EMERGENT COORDINATION BETWEEN HUMANS AND ROBOTS

Utilizing Movement Synchronization to Improve Human-Robot Interaction

TAMARA LORENZ

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Graduate School of Systemic Neurosciences
Ludwig-Maximilians Universität München

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by Dipl.-Ing. Tamara Lorenz
to the Graduate School of Systemic Neurosciences, (GSN)
Ludwig-Maximilians Universität, (LMU)
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THESIS ADVISORY COMMITTEE:
Prof. Dr.-Ing. Sandra Hirche
Prof. Dr. Heiner Deubel
Prof. Dr. Stefan Glasauer

EXAMINATION COMMITTEE:
Prof. Dr.-Ing. Sandra Hirche
Prof. Dr. Heiner Deubel
PD Dr. Agnieszka Wykowska
Prof. Michael J. Richardson, PhD

To those who encouraged me.

ABSTRACT

Emergent coordination or movement synchronization is an often observed phenomenon in human behavior. Humans synchronize their gait when walking next to each other, they synchronize their postural sway when standing closely, and they also synchronize their movement behavior in many other situations of daily life. *Why* humans are doing this is an important question of ongoing research in many disciplines: apparently movement synchronization plays a role in children's development and learning; it is related to our social and emotional behavior in interaction with others; it is an underlying principle in the organization of communication by means of language and gesture; and finally, models explaining movement synchronization between two individuals can also be extended to group behavior. Overall, one can say that movement synchronization is an important principle of human interaction behavior.

Besides interacting with other humans, in recent years humans do more and more interact with technology. This was first expressed in the interaction with machines in industrial settings, was taken further to human-computer interaction and is now facing a new challenge: the interaction with active and autonomous machines, the interaction with robots. If the vision of today's robot developers comes true, in the near future robots will be fully integrated not only in our workplace, but also in our private lives. They are supposed to support humans in activities of daily living and even care for them. These circumstances however require the development of interactional principles which the robot can apply to the direct interaction with humans.

In this dissertation the problem of robots entering the human society will be outlined and the need for the exploration of human interaction principles that are transferable to human-robot interaction will be emphasized. Furthermore, an overview on human movement synchronization as a very important phenomenon in human interaction will be given, ranging from neural correlates to social behavior. The argument of this dissertation is that human movement synchronization is a simple but striking human interaction principle that can be applied in human-robot interaction to support human activity of daily living, demonstrated on the example of pick-and-place tasks.

This argument is based on five publications. In the first publication, human movement synchronization is explored in a goal-directed tasks which bares similar requirements as pick-and-place tasks in activities of daily living. In order to explore if a merely repetitive action of the robot is sufficient to encourage human movement synchronization, the second publication reports a human-robot

interaction study in which a human interacts with a non-adaptive robot. Here however, movement synchronization between human and robot does not emerge, which underlines the need for adaptive mechanisms. Therefore, in the third publication, human adaptive behavior in goal-directed movement synchronization is explored. In order to make the findings from the previous studies applicable to human-robot interaction, in the fourth publication the development of an interaction model based on dynamical systems theory is outlined which is ready for implementation on a robotic platform. Following this, a brief overview on a first human-robot interaction study based on the developed interaction model is provided. The last publication describes an extension of the previous approach which also includes the human tendency to make use of events to adapt their movements to. Here, also a first human-robot interaction study is reported which confirms the applicability of the model.

The dissertation concludes with a discussion on the presented findings in the light of human-robot interaction and psychological aspects of joint action research as well as the problem of mutual adaptation.

ZUSAMMENFASSUNG

Spontan auftretende Koordination oder Bewegungssynchronisierung ist ein häufig zu beobachtendes Phänomen im Verhalten von Menschen. Menschen synchronisieren ihre Schritte beim nebeneinander hergehen, sie synchronisieren die Schwingbewegung zum Ausgleich der Körperbalance wenn sie nahe beieinander stehen und sie synchronisieren ihr Bewegungsverhalten generell in vielen weiteren Handlungen des täglichen Lebens. Die Frage nach dem *warum* ist eine Frage mit der sich die Forschung in der Psychologie, Neuro- und Bewegungswissenschaft aber auch in der Sozialwissenschaft nach wie vor beschäftigt: offenbar spielt die Bewegungssynchronisierung eine Rolle in der kindlichen Entwicklung und beim Erlernen von Fähigkeiten und Verhaltensmustern; sie steht in direktem Bezug zu unserem sozialen Verhalten und unserer emotionalen Wahrnehmung in der Interaktion mit Anderen; sie ist ein grundlegendes Prinzip in der Organisation von Kommunikation durch Sprache oder Gesten; außerdem können Modelle, die Bewegungssynchronisierung zwischen zwei Individuen erklären, auch auf das Verhalten innerhalb von Gruppen ausgedehnt werden. Insgesamt kann man also sagen, dass Bewegungssynchronisierung ein wichtiges Prinzip im menschlichen Interaktionsverhalten darstellt.

Neben der Interaktion mit anderen Menschen interagieren wir in den letzten Jahren auch zunehmend mit der uns umgebenden Technik. Hier fand zunächst die Interaktion mit Maschinen im industriellen Umfeld Beachtung, später die Mensch-Computer-Interaktion. Seit kurzem sind wir jedoch mit einer neuen Herausforderung konfrontiert: der Interaktion mit aktiven und autonomen Maschinen, Maschinen die sich bewegen und aktiv mit Menschen interagieren, mit Robotern. Sollte die Vision der heutigen Roboterentwickler Wirklichkeit werde, so werden Roboter in der nahen Zukunft nicht nur voll in unser Arbeitsumfeld integriert sein, sondern auch in unser privates Leben. Roboter sollen den Menschen in ihren täglichen Aktivitäten unterstützen und sich sogar um sie kümmern. Diese Umstände erfordern die Entwicklung von neuen Interaktionsprinzipien, welche Roboter in der direkten Koordination mit dem Menschen anwenden können.

In dieser Dissertation wird zunächst das Problem umrissen, welches sich daraus ergibt, dass Roboter zunehmend Einzug in die menschliche Gesellschaft finden. Außerdem wird die Notwendigkeit der Untersuchung menschlicher Interaktionsprinzipien, die auf die Mensch-Roboter-Interaktion transferierbar sind, hervorgehoben. Die Argumentation der Dissertation ist, dass die menschliche Bewegungs-

synchronisierung ein einfaches aber bemerkenswertes menschliches Interaktionsprinzip ist, welches in der Mensch-Roboter-Interaktion angewendet werden kann um menschliche Aktivitäten des täglichen Lebens, z.B. Aufnahme-und-Ablege-Aufgaben (pick-and-place tasks), zu unterstützen.

Diese Argumentation wird auf fünf Publikationen gestützt. In der ersten Publikation wird die menschliche Bewegungssynchronisierung in einer zielgerichteten Aufgabe untersucht, welche die gleichen Anforderungen erfüllt wie die Aufnahme- und Ablageaufgaben des täglichen Lebens. Um zu untersuchen ob eine rein repetitive Bewegung des Roboters ausreichend ist um den Menschen zur Etablierung von Bewegungssynchronisierung zu ermutigen, wird in der zweiten Publikation eine Mensch-Roboter-Interaktionsstudie vorgestellt in welcher ein Mensch mit einem nicht-adaptiven Roboter interagiert. In dieser Studie wird jedoch keine Bewegungssynchronisierung zwischen Mensch und Roboter etabliert, was die Notwendigkeit von adaptiven Mechanismen unterstreicht. Daher wird in der dritten Publikation menschliches Adaptationsverhalten in der Bewegungssynchronisierung in zielgerichteten Aufgaben untersucht. Um die so gefundenen Mechanismen für die Mensch-Roboter Interaktion nutzbar zu machen, wird in der vierten Publikation die Entwicklung eines Interaktionsmodells basierend auf Dynamischer Systemtheorie behandelt. Dieses Modell kann direkt in eine Roboterplattform implementiert werden. Anschließend wird kurz auf eine erste Studie zur Mensch-Roboter Interaktion basierend auf dem entwickelten Modell eingegangen. Die letzte Publikation beschreibt eine Weiterentwicklung des bisherigen Vorgehens welche der Tendenz im menschlichen Verhalten Rechnung trägt, die Bewegungen an Ereignissen auszurichten. Hier wird außerdem eine erste Mensch-Roboter- Interaktionsstudie vorgestellt, die die Anwendbarkeit des Modells bestätigt.

Die Dissertation wird mit einer Diskussion der präsentierten Ergebnisse im Kontext der Mensch-Roboter-Interaktion und psychologischer Aspekte der Interaktionsforschung sowie der Problematik von beiderseitiger Adaptivität abgeschlossen.

CONTENTS

ACRONYMS

ADL activities of daily living

ANOVA analysis of variances

ASYN asynchrony

CPG central pattern generator

CSC cross-spectral coherence (= SI)

CV circular variance

DST dynamical systems theory

DT dwell time

fNIRS functional near-infrared spectroscopy

FREE free actor (non obstacle)

HAMP hampered actor (50% of trials with obstacle)

HC half-cycle = full-distance

HHI human-human interaction

HKB Haken-Kelso-Bunz model

HRI human-robot Interaction

IPL inferious parietal lobule

ITI inter-tap interval

LED light-emitting diode

MASYN mode-related asynchrony

MNS mirror neuron system

MS movement synchronization

MSI mode-related synchronization index

MT movement time

MV median velocity

NOS no synchronization

PEM prediction error minimization, an algorithm of MATLABs System Identification Toolbox

PES phase and event synchronization

PL path length

QC quarter-cycle = half-distance

RMI rhythmic movement interference

RMSE root mean square error

SD standard deviation

SI synchronization index (= CSC)

SMS sensori-motor synchronization

STS superior temporal sulcus

VPI virtual partner interaction

ZC zero-cycle = zero-distance

Part I

INTRODUCTION

1 INTRODUCTION

I can't define a robot, but I know one when I see one...

— Joseph Engelberger

1.1 ROBOTS ENTER THE SOCIETY

Already in the past centuries, interaction between humans and machines gained more and more importance as machines were entering our workplaces, our close surrounding and our homes. This led to disciplines such as ergonomics, human factors, human-machine interaction and lately human-computer interaction, in which the safety and usability of machines are designed and evaluated.

In the 21st century, a new kind of machines is entering our surrounding: robots. Robots are already quite common in industrial settings in which they were introduced in the 1960s (Garcia et al., 2007; IFR, 2012). Thus, considering mainly industrial implications, the ISO 8373 describes robots as "automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications". Considering this, one advantage of robots in comparison to ordinary, passive machines becomes clear: they are activated. Robots have the ability to move and perform complex tasks, independent from individual step-by-step human steering. Furthermore, a typical industrial robot is programmed to repeat the same task over and over again, without getting tired or being at risk of mistakes like a human worker. Thus, an industrial robot is an efficient worker although mostly not very flexible. With regard to the latter, humans are much better in adapting to sudden changes or problems.

However, besides very few examples like the KUKA LWR (Bischoff and Kurth, 2010), commercially available robots are still mostly acting and working behind fences to protect humans from entering into their close surrounding. Nevertheless, large effort is undertaken to enable robots to deal autonomously with their surrounding and to be reliable interaction partners for the human. Therefore, the actual attempt is to bring robots out of their cages and into the daily life of people (Garcia et al., 2007).

Besides industrial applications, the robots' arising autonomy also qualifies them to assist in tasks that are so far limited to human support, such as personal assistance and care (Bemelmans et al., 2012;

Brose et al., 2010) (but see Frennert and Östlund (2014)). Possible applications are manifold: robots are supposed to enter both the private and the public domain. In the private sector they could be helpers in the household (Iocchi et al., 2014; Parlitz et al., 2007), support aging in place (Bemelmans et al., 2012; Graf et al., 2009; Schroeter et al., 2013) or merely serve for entertainment (Fujita, 2001). In the public sector they are supposed to be present in clinical settings like surgery (Autorino et al., 2013; Brody and Richards, 2014) or rehabilitation (Cooper et al., 2008; Maciejasz et al., 2014), as teachers (Fridin, 2014; Scassellati et al., 2012) or simply as guides, for example in museums (Burgard et al., 1999; Thrun, 2004).

1.1.1 *Robots as Assistants for Activities of Daily Living*

One characteristic robots are often associated with is their ability to assist humans in activities of daily living (ADLs) (Begum et al., 2013; Guidali et al., 2011; Schweighofer et al., 2012). Activities of daily living are actions that most people are performing as routine tasks throughout their day. They include caring for oneself, but also interaction with household devices, cleaning and tidying (Pendleton and Schultz-Krohn, 2013). Activities of daily living are often composed of sub-tasks: for example making a cup of tea requires to pick a cup from the shelf, placing it on the table, picking up a tea bag, putting it into the cup, picking up the water boiler, pouring water into the cup, etc. Further classic tasks are for example picking up things from the floor, placing an item in a shelf or setting dishes on a table. And although these tasks appear very simple, they are the underlying requirement for more complex tasks like self-hygiene, cleaning the house or cooking. What becomes prevalent here is that all of these tasks usually require the action of picking and placing objects. Therefore, these tasks are called *pick-and-place tasks*.

If a pick-and place task is to be performed alone, the basic behavioral requirements are the following:

- pick-and-place tasks are often *repetitive* tasks; usually there are several objects to be picked up from one location and to be put to another location.
- pick-and-place tasks are *cyclic* tasks; this means that the movements from picking up an object to placing it down and reverse are formed by one movement trajectory with a defined beginning and a defined end.
- pick-and-place tasks require *goal-directed* actions; those are precise movements towards an objects location (or target) in order to pick it up and move it to another defined location in which precision in positioning again plays a role.

People who cannot cope with these activities alone anymore either need assistance (like for example elderly people, see Begum et al. (2013)) or need to relearn these activities due to motor incapability after injury or stroke (Guidali et al., 2011; Schweighofer et al., 2012). As pick-and-place tasks are the basic actions for many general actions, they are among the most important tasks to be trained, relearned or supported in order to reestablish a higher quality of living (Maciejasz et al., 2014; Stanger et al., 1994; Tsui et al., 2008). Usually this training and the relearning is supported by a therapist, but also here, robots are increasingly important (Maciejasz et al., 2014).

The traditional approach for training pick-and-place tasks usually requires physical guidance by the help of a therapist. However, Ganesh et al. (2014) showed that people not only profit from pure guidance during haptic interaction, they additionally capture additional task-related information of their partner which enabled them to improve their performance error to a higher extend in the given time. Although claimed for haptic interaction, Ganesh et al.'s notion is supported by the action observation therapy introduced by Ertelt et al. (2007). The action observation therapy makes use of the idea that the human brain does not only process motor information when we actually move, but also when we observe movement (Kim, 2013), see also Section 1.2.3. In a study with stroke patients, Ertelt et al. showed that by priming physical training with action observation of daily life tasks, the motor function of the upper limb was significantly improved when performing these actions. Thus, only viewing and performing a pick-and-place task jointly with another actor can improve the ability to perform the task, which potentially works in the interaction with a robot as well.

Besides their therapeutic use, robots are furthermore thought to be servants in household tasks which will require them to coordinate their actions in close surroundings with humans, e.g. while setting a table, cooking or assisting in any other activity of daily living (Lemaignan et al., 2012). Again, these activities are mainly pick-and-place tasks to be performed during interaction in a joint action space.

Thus, if the pick-and-place task is to be carried out together with an interacting agent, be it a humans or a robot, further criteria play a role:

- both actors have to coordinate their motions in space and time.
- the coordination should be smooth.
- the actions of each agents should be predictable.
- collisions are to be avoided.

Furthermore, if a pick-and-place task should be performed together with a robot, it is not sufficient to simply design a passive human ma-

chine interface based on the already established principles from traditional ergonomics or human-computer interaction (Fernaeus, 2009; Young et al., 2011). It still matters, how the machine (the robot) is designed and how the information is exchanged with the human. Additionally of course safety plays a major role. However, the robot has to be able to coordinate its actions with those of the human in goal-directed tasks (Dautenhahn, 2007; Jarrassé et al., 2012; Marin et al., 2009).

Note: Although grasping might be considered as the key action during a pick-and-place task, it was found that human reaching movements are influenced by the object that has to be grasped (Baldauf and Deubel, 2010; Rosenbaum and Jorgensen, 1992). In the following the focus will therefore be on reaching movements and how they are altered and influenced in emergent human-human and human-robot interaction and leave grasping and prehension during behavioral coordination to future research.

1.1.2 *From Human-Human to Human-Robot Interaction*

If a robot is supposed to coordinate its movements with those of a human, it needs to be able to predict human actions and react appropriately. In this context, a common approach is to create robot interaction principles by biological inspiration - i.e. by designing the robots' actions based on human action principles (Fong et al., 2003). The underlying hypothesis is that humans would prefer to interact with robots in the same way as they interact with other humans. The advantage of this seems obvious: usually humans are able to coordinate their actions with other humans without reflecting on it. Thus, humans would not need an instruction to interact with the robot and even naïve people who never saw a robot before are able to immediately and naturally interact with it because the robot behaves like they expect it (de Kleijn et al., 2014; Marin et al., 2009).

Thus, the first objective of this work is to provide an overview on human interaction research and to introduce different hypothesis on how humans coordinate their actions (human-human interaction, HHI). Here, an emphasis is put on underlying principles that usually are beyond human conscious recognition during coordination. Following this, minimal requirements are defined for including these findings to human-robot interaction (HRI) in goal-directed pick-and-place tasks. These requirements are then the point of origin for the line of research presented in the publications which form the main body of this work, spanning from the exploration of human movement coordination in goal-directed tasks to modeling human behavior and testing the implemented model in an HRI-setting.

Note: In this work, goal-directed actions are understood as actions that are goal-directed in terms of their environmental constraints and

thus require precisely moving towards certain targets in which objects could be located.

1.2 HUMAN INTERACTION PRINCIPLES

Humans interact with each other in multiple ways. However, be it carrying a big object together or only greeting each other, all human interactions require some kind of informational exchange. This information exchange can be tactile such as when inducing a new motion direction while moving an object together (Mörtl et al., 2012), auditory by use of noise or language (Lagarde and Kelso, 2006; Toni et al., 2008), or merely visual by observing the other's action (Vlaskamp and Schubö, 2012). In the following, the focus will be on visual information exchange as vision is the most important perceptual channel for coordinating actions in a pick-and-place task.

1.2.1 *Joint Action and Emergent Coordination*

In human behavioral research, the interaction between two agents is often referred to as joint action. Joint action takes place when two agents coordinate their movements in space and time in order to change the states of their surrounding (Sebanz et al., 2006). However with regard to the question *how* this joint action is created between interaction partners, there exist competing hypotheses:

- the *cognitive* approach which is rather a causal and computational (i.e. logical, linear) approach;
- the *embodied-embedded* or *ecological* approach which follows the ideas of dynamical systems and self-organization (i.e. non-linear).

The biggest divergence between these two approaches can be explained best by the way they treat the notion of action representation. According to the cognitive approach, humans perceive the world and form a (neural) representation of the actual task and the changing environment. This representation of the task is mapped onto the representation of the own abilities and shapes the actions executed in response to the perception (perception-action matching) (Knoblich et al., 2011; Prinz, 1997). Thus, for successful joint action, people have to jointly attend to objects or events in their surrounding and thus know what lies in the field of own and other perception, i.e. they know what the other person *can* do. Furthermore, based on the representation of possible actions they form a prediction about what the other agent *should* do and observe the ongoing actions and thus know what the other *actually does*. This enables them to attune their own actions to those of the interaction partner (Sebanz et al., 2006) by means of error correction. As this is the same for both interaction partners,

they thus *share* this representation which allows them to manage coordination (Sebanz et al., 2005; Vesper et al., 2014).

In contrast, the embodied-embedded approach claims that people interact with their surrounding based on constraints that the environment provides (i.e. the task, the interaction etc.). The agents are embodied in the sense that they have a body which is organized in a physical and biological way and this body is embedded in a world that provides perceivable information and follows physical constraints (e.g. dynamics) (Keijzer, 2002; Marsh et al., 2009; Warren, 2006). According to this principle, humans perceive their surrounding based on affordances (action possibilities) which can be followed by necessary reactions (Heft, 1989; Shaw, 2003). During joint action, one agent becomes embedded in a social unit with the other agent. Thus, based on mutual coupling the two individuals are pulled into forming a dyad which causes dynamic interactions that have a certain resistance to change after perturbation (i.e. hysteresis, bifurcation) (Marsh et al., 2009; Richardson et al., 2007a). Taken together, the embodied approach claims that actions and reactions emerge based on principles of self-organization and can be described by their dynamics which emerge due to internal and external requirements. Hence, a representation of the task in the cognitive sense is not necessary (Warren, 2006).

With regard to this notion, the biggest concern from the cognitive psychology side is that tasks that require complex sequences or complementary actions might not be covered by the embodied approach (Sebanz and Knoblich, 2009a). However, Keijzer (2002) suggests the inclusion of internal control parameters that could both be shaped by affordances or even a representation in the cognitive sense, and would thus bridge the gap between the two approaches.

Also trying to include both approaches, Knoblich et al. (2011) distinguishes between planned coordination and emergent coordination: planned coordination is given when two agents interact and both plan their own actions in relation to the intended outcome of the joint action and/or the actions of the respective other agent, which is the cognitive approach. Additionally however, the authors acknowledge the existence of emergent principles which occur spontaneously based on self-organization. Knoblich et al. (2011) claim that emergent coordination is a profound explanation for tasks that require quick temporal coordination and can therefore be included in planned coordination. However, emergent coordination is also observed independently of planned coordination and can be described by four source categories: entrainment, affordances, perception-action matching and action simulation.

Here, *perception-action matching* and *action simulation* are closely related concepts which describe emergent behavior from a cognitive perspective. First, one perceives an action that is performed by the

other person which leads to the formation of an action representation in the observer. As apparently the same neural structures are responsible for action understanding and action production, this match leads to emergent coordination, see Section 1.2.3. Once this match is established it allows the observer to apply predictive models (action simulation) on the behavior of the other's actions or the actions of the interaction entity (Knoblich and Sebanz, 2008; Wolpert et al., 2003) - and thus leads to emergent coordination unfolding to future behavior. Besides, it also allows for adaptive error correction (Shadmehr et al., 2010). *Affordances* are the action opportunities or requirements of objects or the environment. For emergent joint action this means that if two people e.g. see an object, they attribute the same affordances to it and – without further explicit information exchange – are able to start a joint action with regard to the object (e.g. carrying a large object together that one person cannot carry alone (Isenhower et al., 2010; Richardson et al., 2007a)). Finally, *entrainment* is the emergence of temporal coordination of actions due to information exchange (in the ecological sense). This information exchange can be tactile based physical coupling, but entrainment also happens when people only see or hear each other, see Section 1.2.2.

Overall, planned and emergent coordination might be interlinked in a way in which planned actions cover those aspects that lead to an outcome of the task, such as the sequence and spatial order of things in a pick-and-place task, while emergent coordination is likely more concerned with the online temporal coordination of actions between people. Here, agents may be treated as a coordinated (coupled) entity because their behavior is driven by the same cues and motor routines (Knoblich et al., 2011; Spivey, 2007). Although the sources for planned coordination and emergent coordination seem to be quite distinct, Knoblich et al. (2011) claim that if one plans an action, one most often also recruits the functionality of the fast mechanisms of emergent coordination. They even claim emergent coordination to be the key facilitator of every joint action.

Thus, emergent behavior is a fundamental feature of human interaction. Especially for maneuvering temporal aspects of action coordination, like when alternately picking and placing objects in a joint workspace, movement entrainment is a key phenomenon.

1.2.2 *Entrainment and Human Movement Synchronization*

A very typical form of entrainment that emerges during repetitive tasks jointly performed by two humans, is movement synchronization (Schmidt and O'Brien, 1997; Schmidt and Richardson, 2008). Movement synchronization emerges as soon as people exchange visual, acoustic or tactile information (Lagarde and Kelso, 2006) and even if people are instructed to avoid synchronizing their movements, this

seems impossible (Issartel et al., 2007; Schmidt and O'Brien, 1997). One interesting example showing that movement synchronization is actually an unconsciously but constantly emerging phenomenon is postural coordination. If humans stand, they actually do not stand completely still, instead they sway as a result of balance control (Shockley et al., 2003; Varlet et al., 2011). Exploring this finding in a joint task in which two persons were solving a puzzle together, Shockley et al. (2003) could show that their postural sway becomes synchronized.

In the past decades, movement synchronization was furthermore studied in multiple tasks like rocking in chairs (Richardson et al., 2007b), walking side-by side (van Ulzen et al., 2008), swinging pendulums (Richardson et al., 2005), arms (Issartel et al., 2007; Richardson et al., 2009) or legs (Schmidt et al., 1990) or tapping fingers (Repp, 2005).

Similar to the two competing approaches with regard to joint action in general, there are two different approaches when it comes to the explanation of temporal organization in movement synchronization. According to the cognitive approach, movement synchronization between two interaction partners is established by means of continuous perception-action matching that is adapted based on subsequent error correction. Support for this notion comes from studies on sensorimotor synchronization (Konvalinka et al., 2010; Repp, 2005; Repp and Su, 2013). In repetitive interactive tapping, it is hypothesized that the time between two taps (events) is adjusted on a sequential basis, i.e. that the observation of the current inter-tap interval (ITI) of the interaction partner is used to correct and adjust the own subsequent ITI (Konvalinka et al., 2010; Repp and Su, 2013). Thus, due to mutual adaptation of subsequent ITIs, synchronization is organized. In sensorimotor synchronization, the timing of actions is usually captured by means of stochastic models (Schöner, 2002; Wing and Kristofferson, 1973).

In contrast, the ecological approach claims that timing is a dynamic process which can be described as non-linear differential equations (Haken et al., 1985; Schöner, 2002). Here, the interaction between two individuals can be captured by the dynamics of coupled oscillations and hence the common approach is to describe the difference in timing by means of a difference in the phase of the movements, the relative phase. This relative phase is governed by a dynamical system which is attracted to a stable phase relation (attractors, states), which are the limit cycles of the coupled oscillator system. The synchronization process itself is described as frequency detuning of the two individual oscillators' eigenfrequencies due to their coupling. In the context of coordination it was found that this concept explains both intra- and interpersonal interaction (Schmidt et al., 1990). Furthermore, in both cases there are two stable states, namely in-phase relation (no phase difference) and anti-phase relation (a phase

difference of π) between the two action sequences (Kelso et al., 1981; Schmidt et al., 1990), see also Section 1.4.2.

Considering both approaches, there is a debate going on whether especially repetitive movements are organized by means of discrete event perception, and thus by representation of these events, or if the organization is continuous (Delignières and Torre, 2011; Repp and Steinman, 2010; Studenka and Zelaznik, 2011; Torre and Balasubramaniam, 2009). In this context, even two distinct timer models are considered - one for continuous and one for discrete movements, namely emergent and event-based timing respectively (Delignières and Torre, 2011; Torre and Balasubramaniam, 2009). In support of this idea of two independent timer models, Spencer et al. (2003) showed that people with cerebellar lesion were still able to temporally control continuous movements, while the temporal control of discrete movements was restricted, see also (Schaal et al., 2004). However, while Delignières and Torre (2011) claim that these two timer models are mutually exclusive and only recruited based on task demands, Repp and Steinman (2010) assume that emergent and event-based timing can coexist in a dual task situation. The latter also supports the findings of Studenka and Zelaznik (2011) who showed that including vs. omitting events from a task (i.e. the table surface for tapping or a marked position in a circle drawing task) allows for easier synchronization to an external stimulus. Here, events can be instrumented for adaptation on a cycle-to-cycle basis while oscillations can still be adjusted based on phase adaptation (by means of velocity adjustments) on a within cycle basis (Torre and Balasubramaniam, 2009).

Overall, for a repetitive pick-and-place task both timer models may play a role and might even benefit from being connected.

Note: Although entrainment and movement synchronization are often used synonymously, synchronization precisely would be the state when period and phase of a signal are matched exactly, while entrainment only refers to the matching of period, but allows for a phase difference between signals (Kelso et al., 1981). However, in line with the common agreement and because this work refers to movement synchrony both at zero phase difference (in-phase) and a phase difference of π (anti-phase), entrainment and synchrony will still be used synonymously in the following. Besides, synchronization is sometimes used synonymously with (social) coordination.

1.2.3 *Neural Implications*

As outlined in Section 1.2.1, the matching of perception and action plays a major role for successful joint action. The neural substrates that are most often associated with the transformation from perception to action and also with the recognition and interpretation of action is the mirror neuron system (MNS).

Originally, the mirror neuron system was discovered in monkeys (Rizzolatti and Craighero, 2004). Here it was found that neurons in the area F5 of the premotor cortex of the monkeys fire both upon action perception and action execution. Later, a comparable system was also discovered in the human brain (Gallese et al., 2004; Rizzolatti, 2005). Apparently, in the human mirror system the visual information is first processed in the superior temporal sulcus (STS) which translates visual information to *motor format* before sending it to the inferior parietal lobule (IPL) which then forms the action perception matching together with the premotor areas for action execution (Cattaneo and Rizzolatti, 2009; Chersi, 2011). However, while the monkey's brain is only activated during the observation of transitive actions (those with an outcome like getting food), the MNS in humans is also active in intransitive movements which might or might not be meaningless, but allow for the human ability to imitate actions (Fadiga et al., 1995; Rizzolatti, 2005). Thus, the human MNS plays a major role in the coordination of action and motor learning (Cattaneo and Rizzolatti, 2009).

Most often the MNS is associated to account for the so called *common coding* approach. That is, as described in Section 1.2.1, the theory that humans form a common representation (in the cognitive sense) of the task they perform. In this, the MNS would be an enabler both for a representation of the action of the other person by simulating (mirroring) these actions and additionally an enabler for matching the own actions to this perception by providing the simulation of the own action plan. Besides, the MNS would account for predictions that are necessary for forming follow-up plans and for online adaptation to perceived action, and thus enable a flexible interpersonal coordination in real-time (Colling et al., 2013; Pacherie and Dokic, 2006; Sebanz and Knoblich, 2009b).

In line with this are findings with regard to movement interference: if people watch movements that differ in space to those performed by themselves, a so called *interference effect* can be observed (Brass et al., 2001; Kilner et al., 2003; Sebanz et al., 2003; Stanley et al., 2007). The interference effect increases movement onset and reaction times in response to the observed incompatibility (Brass et al., 2001; Sebanz et al., 2003), but it also affects the actual movement execution (Kilner et al., 2003; Stanley et al., 2007). It is hypothesized that while performing the own action, a simultaneous activation of the human MNS causes some kind of *motor contagion* (Blakemore and Frith, 2005). By observing somebody else's action and activating one's representation of it, the own action is facilitated. However, if the observed action is incongruent to the representation of the own executed movements, this might create additional load as incorrect motor programs have to be inhibited. For the actual execution of movement this means that people tend to unintentionally mirror the movements they see, while

they actually intentionally try to perform a different movement. This conflict is hypothesized to cause the deviation. How movement interference might affect movement performance in a pick-and place task is, among other aspects, explored and discussed in Chapter 6.

An alternative explanation for the observed deviations from the instructed plane of motion when observing somebody performing movements incongruent to one's own, is provided by the notion of *rhythmic movement interference* (RMI) (Richardson et al., 2009; Romero et al., 2012). The crucial point in RMI is that these deviations actually reflect that people recruit additional movement degrees-of-freedom in order to stabilize the coordination and increase the task-specific flexibility (Fink et al., 2000), see also discussion in Chapter 6. Thus, the deviations that are considered problematic errors with the cognitive approach are actually described to be supportive for coordination according to this alternative.

This explanation can well be integrated into the ecological perspective which also acknowledges the contribution of the mirror neuron system to human coordination. Here however, the main idea is that the MNS can be treated as a neural network in the brain which shows comparable dynamical features like other complex systems. Here, phase transitions between different modes appear - which was taken as proof that also the brain shows patterns of self-organization (Kelso et al., 2013; Oullier and Kelso, 2009). Here it is especially interesting that the observed transitions happen in parallel with transitions in human behavior (Jantzen et al., 2009; Kelso et al., 2013). Besides, using a dual-EEG Tognoli et al. (2007) identified the *Phi Complex*, a brain signal which is obviously a neuro-marker for action coordination. The Phi Complex results from neural activities in the area of the MNS and is divided into two signals: Phi1 and Phi2. Here, Phi1 is activated in single action and hypothesized to have an inhibiting function towards the mirror neuron system (which is claimed to be always active by default (Brass and Heyes, 2005)), while Phi2 was measured during movement synchronization (Oullier and Kelso, 2009; Tognoli et al., 2007).

Evidence that the MNS is actually involved in movement coordination during activities of daily living beyond reduced laboratory settings comes from a brain imaging study (functional near-infrared spectroscopy, fNIRS) in which two people were jointly setting a table (Egetemeir et al., 2011). It was found that the magnitude of neural activity was higher in the joint action condition compared to the single action condition which underlines again that an interaction with another person is processed different compared to the same action performed alone. In this line, there is recent evidence in cognitive psychology that the interaction with another person is actually not represented as a task in which one person (*me*) interacts with another person (*you*). Instead, the interaction is represented and processed as

a part of a joint action (*me+x* or maybe even *we*) (Kourtis et al., 2013; Sebanz et al., 2005; Vesper et al., 2010), which links back to the ecological perspective in that the interaction cannot be observed in pieces but has to be treated as an entity.

1.2.4 *Social Implications*

Besides exploring *how* synchronization is established, another important question is *why* movement synchronization emerges. If synchronization is such a frequently emerging phenomenon between humans, and even observed in other species and systems (Strogatz, 2003), it must serve a purpose.

One is that people obviously make themselves more predictable to their interaction partners by reducing the variability in one's own movements by means of synchrony (Vesper et al., 2011). Furthermore, movement synchrony was shown to increase our perceptual sensitivity to others (Macrae et al., 2008) and to tasks we have to perform together (Valdesolo et al., 2010). Support for this notion comes from the idea that the interacting dyad can be treated as an interaction entity. Thus, although the interaction is characterized by lots of degrees of freedom, the coordination becomes easier to deal with by linking them into action synergies (Riley et al., 2011).

Besides, research in social science and related areas indicates that movement synchronization and other related emergent processes like mimicking and imitation are not only there to facilitate human coordination and enable to learn from each other (Iacoboni, 2009; Meltzoff, 2005), they furthermore play a major role in forming connections between people and thus creating emotion and social understanding which can even lead to social bonding (Wheatley et al., 2012).

In this context it was shown that synchronous behavior is related to the emergence of compassion (Hove and Risen, 2009; Semin, 2007; Valdesolo and Desteno, 2011) and positive emotions towards another person (Wiltermuth and Heath, 2009). If we act in synchrony with each other we see that the other person is acting *like us*, which creates a feeling of similarity and rapport (Semin, 2007; Valdesolo et al., 2010). Vice versa, a greater feeling of rapport and sympathy between two individuals can also be measured by the degree to which they synchronize (Miles et al., 2009).

Although synchrony usually emerges unintentionally it can of course be induced and even *engineered* (i.e. constructed) to gain positive emotional effects between people, for example while marching or singing together. In the reverse case, when breaking the flow of synchronization, humans usually take this as a means for non-verbal communication of their intentions (Wheatley et al., 2012).

In the realm of human-robot interaction, these findings are very promising. It is most likely that a positive relation which emerges due

to emergent coordination in HHI can be engineered in the original meaning of the word, namely by designing a robot in such a way that movement synchronization also emerges in HRI (Marin et al., 2009).

Therefore, besides aiming for understanding human emergent coordination in goal-directed tasks, the problem approached within this work is whether movement synchronization can be engineered for HRI such that it naturally emerges in the same way as it emerges between humans. If this is possible, it can not only lead to improved human-robot joint task performance in pick-and-place tasks and thus support human activities of daily living, it could additionally enable a social relation between the human and the robot and thus increase the motivation to interact with it, e.g. in physical rehabilitation.

1.3 MINIMAL REQUIREMENTS FOR EMERGENT COORDINATION IN HUMAN-ROBOT INTERACTION

Overall, one can say that emergent behavior and movement synchronization especially, play an important role in human life. It creates our social embedding and is guided by internal (neural, perceptional) and external (social, affordances) factors. But most importantly, and regardless of how the underlying processes interact, the fact that emergent behavior is a phenomenon that humans mostly do not reflect about but still enables smooth interaction, makes it a very interesting phenomenon for the interaction with robots (Marin et al., 2009). Besides, if emergent behavior between humans and robots could additionally create a kind of social feeling, this would be beneficial for the acceptance of robots in the human environment and on the long run for the motivation to interact with it. Acceptance and motivation to interact are especially important in rehabilitation and therapy (David et al. (2014),Lorenz et al. (submitted)), but of course also for economical reasons (Barnett et al., 2014). If the robot is not accepted and cannot motivate interaction, it will not be used (Mitzner et al., 2010). If it is not used, it will not be maintained or bought.

Furthermore, if movement synchronization naturally emerges between humans and robots during movement coordination, this may solve several issues of HRI in repetitive tasks: synchronized movements increase predictability (Vesper et al., 2011) and thus safety of the interaction: the robot *behaves* like its human interaction partner expects, and thus no insecurity, hesitation or arbitrary behavior arises. Thus, enabling emergent coordination can improve human-robot joint task performance and induce the human's acceptance of the robot as social interaction partner.

However, if we want to enable movement synchronization in a human-robot setting, some important aspects have to be considered, both from the human's and the robot's perspective.

1.3.1 *Human Perspective*

From what was outlined in the previous sections, one can infer the large number of processes that are involved in the emergence of human-human movement synchronization. It was shown that perceptual exchange plays a crucial role and that seeing each other perform an action is essential for the emergence of synchronization between humans (Richardson et al., 2005; Schmidt et al., 2007). Thus, in the following the exploration of human-human as well as human-robot interaction is arranged in a setup that guarantees both interaction partners to always have full visual access to the behavior of each other.

Even though interaction partners have to be close to allow for movement synchronization to emerge, it was shown that an overlapping workspace shapes the action parameters of two interacting humans (Vesper et al., 2009). Thus, the reported experiments do not require spatial coordination and active collision avoidance. Although interaction partners are acting in a close workspace which is shared in terms of a shared peripersonal space (Previc, 1998), the movements of the agents are not overlapping.

When seeing another person perform an action, and regardless of being the cause or the result of the synchronization process, the mirror neuron system is active in movement coordination and even reflects the emergence of joint action (Section 1.2.3). Thus, it is important to consider if and when robotic actions provoke mirroring. With regard to the interaction with robots, it was shown that the mirror neuron system actually mainly responds to biological motion in the sense that it reacts to human-like motion profiles (Chaminade and Cheng, 2009; Press, 2011). Thus, a correct implementation of human-like motion trajectories seems essential for the emergence of coordinated action. In this context it was shown that the implementation of minimum-jerk trajectories are a good estimate of human-like behavior (Flash and Hogan, 1985) and people exhibit comparable effects like movement interference (Kilner et al., 2007) or decreased reaction times (Huber et al., 2013) in response to them. Biological motion furthermore includes that the trajectories for reaching from one point to another are bell-shaped and cross a via-point in the highest elevation in which also maximal velocity is reached (Flash and Hogan, 1985). Here, the elevation of the movement is already a signal for the interaction partner with regard to the landing position (Vesper, 2014; Vesper and Richardson, 2014). In addition, biological motion is associated with uncertainty. Apparently there are so-called micro-movements, small movements that can be interpreted as motor noise, that shape human perception of biological motion and contribute to the inference of intentional movements (Scholl and Tremoulet, 2000; Tremoulet and Feldman, 2006). If we want humans to perceive robotic

actions as human-like, a certain variability should thus be included into the motion profile as well.

1.3.2 *Robot Perspective*

If movement synchronization is supposed to emerge between humans and robots, there are certain requirements that have to be fulfilled from the robot side as well.

First, the robot has to know its location in space and the location of the objects and the interaction partner. Furthermore, it has to be able to online capture the changing environment and react appropriately i.e. to human behavior. Thus, the robot needs its own perception-action loop. In the following, the ability to online perceive human action (and in Chapter 8 also objects) will be outsourced to a motion tracking system, see Section 3.1. In future applications and depending on processing time, the use of robotic vision systems and image processing, eventually in combination with embodied perception-action networks, will be necessary to enable the robot to move freely among people (Hoffman, 2012; Yan et al., 2013). However, this is beyond the scope of this work.

The second important requirement from the robot's perspective is its necessary ability to appropriately react to the perceived actions. One possibility is that the robot only executes repetitive actions that are goal-directed in the sense of the required task and avoids collision to the interaction partner and to the objects in the environment. From the robot's perspective, this would be the 'easiest' way to engage in a joint action task. However, for the human, this would require to adapt to the robot's movement parameters like frequency and speed. Thus, the human would have to take over the whole adaptation effort, which means that the emergence of synchronous coordination would depend on the human ability and (unconscious) will to do so. To test this possibility, in Chapter 5 an experiment is reported with which the emergence of movement synchronization is tested between a human and a robot that moves at a defined frequency. Results reveal that movement synchronization does not emerge which can be caused by many different features ranging from the robot's appearance to its motion profile (see Section 9.1). However, one feature that is frequently mentioned in the literature as a key component for emergent behavior, which to the best of my knowledge was not employed and tested in human-robot goal-directed coordination so far, is the notion of *mutual adaptation*[1] (Konvalinka et al., 2010; Marin et al., 2009). Mutual adaptation is the ability of both interaction partners to perceive the other's behavior, especially the behavioral changes, and react to these in such a way that the joint behavior changes towards a

1 Mutual adaptation is also sometimes referred to as bidirectionality of behavior, (mutual) feedback or reciprocity

different state. Thus, it describes the mutual reactions to perceptual feedback taken from the interaction process.

If a robot is supposed to be part of a mutual adaptation process it requires an implementable formal description of which parameters of its own actions it should adapt in reaction to which behavior of the human. Thus, a mathematical model of human synchronization behavior is required that can be implemented on a robotic platform.

1.4 MODELING EMERGENT BEHAVIOR

1.4.1 *Existing Approaches on Emergent Coordination with Robots*

Although there is a substantial body of literature treating emergent coordination based on physical information exchange (see for example Ganesh et al. (2014); Hale and Pollick (2005); Jarrasse et al. (2013); Maeda et al. (2003); Ronsse et al. (2011)), only few tackle joint coordination based on visual information transfer. Emergent coordination is also studied for the coordination of robot teams (Billard and Dautenhahn, 1998; Nadel et al., 2004; Prepin and Revel, 2007; Revel and Andry, 2009) or even multiple robots in swarms (Trianni and Nolfi, 2009; Yan et al., 2013).

One interesting approach in this regard is the model for robot-robot interaction developed by Revel and Andry (2009). Here, the interaction is described as a neural network architecture and is modeled as oscillators made of two neurons coupled by an inhibition parameter. If this factor is chosen as positive, the system synchronizes to in-phase relation while a negative coupling leads to anti-phase relation, which the authors determine as simple turn-taking. This model is successfully implemented to the robotic platform ADRIANA (Prepin and Revel, 2007) and shows emergent arm movement coordination between the two robots. Linking this to human-robot interaction, the emerging synchronization based on the model was utilized to capture the attention of a human in order to establish subsequent interaction (Hasnain et al., 2013) and as a reward signal for learning by imitation (Grand et al., 2014), see also Alissandrakis et al. (2006).

Besides, there are attempts to model emergent synchronization between humans and robots in drumming tasks that are used to study human-robot interaction in terms of social aspects including imitation and turn-taking behavior. Kose-Bagci et al. (2008) use probability functions to determine turn-taking strategies between a human and the humanoid robot Kaspar, while Cicconet et al. (2013) established a vision-based synchronization approach for human-robot joint drumming using movement acceleration for prediction. Furthermore, (Kotosaka and Schaal, 2001) suggest synchronization to an external sound utilizing neural oscillators that are synchronized based on phase difference adjustments. However, although the authors state

that the system can handle several kinds of periodic input, like sound, force and visual stimuli, so far no proof was given that this system is also applicable for coordination in a real human-robot setting.

Albeit being interesting approaches, all of the above mentioned works focus on the emergence of synchrony as a transitive enabler for further action - and not as a principle for applied coordination in a goal-directed activity like a pick-and-place task.

As outlined in Chapter 2, the approach of the current work is to use human interaction data to develop a behavioral model for the goal-directed interaction process. One possibility to describe emergent human behavior in general, and human movement coordination in specific, is by means of the dynamical systems theory (DST) (Schmidt and Richardson, 2008).

1.4.2 *Dynamical Systems Theory for Human Movement Synchronization*

In the beginning of the 1980's, Kelso et al. (1981) explored the basic principles of rhythmic bimanual limb coordination and showed that phase relation between the limbs follows the same characteristics as limit cycle oscillators. Kelso and colleagues furthermore observed that if the two limbs are described as the phase relation of coupled oscillators, there exist two stable attractor states for the emerging coordination, namely in-phase (0° phase shift, both limbs are at the same displacement at the same time) and anti-phase relation (180° phase shift, both limbs are at the reverse displacement at a given time instant). When the frequency of the coordinated action is increased, this leads to a phase transition from the less stable attractor, the anti-phase relation, to the more stable attractor, the in-phase relation (Kelso, 1984).

This observation led to the description of the nonlinear dynamics of bimanual movement coordination by capturing the relative phase angle between the limbs at move.This modeling description became known as the Haken-Kelso-Bunz Model (HKB) (Haken et al., 1985), given by

$$\dot{\Phi} = -a \sin \Phi - 2b \sin 2\Phi, \tag{1}$$

where $\dot{\Phi}$ is the temporal change of the relative phase angle Φ between the two limbs (modeled as oscillators) and a and b are coefficients which capture the coupling strength between them. In order to account for different eigenfrequencies ω of the limbs, the model was extended to

$$\dot{\Phi} = \Delta\omega - a \sin \Phi - 2b \sin 2\Phi, \tag{2}$$

in which $\Delta\omega$ is the intermediate frequency the two systems detune to (Fuchs and Kelso, 1994). Originally developed to describe *intra*-personal bimanual limb coordination, it was later shown that this

mathematical description of the interaction dynamics also holds for *inter*personal movement coordination, which is the interaction between two individuals (Schmidt et al., 1998, 1990).

The HKB-model was developed based on data in which participants were instructed to move in synchrony. Thus, to capture behavior in more realistic settings, it was tested whether the model also captures the dynamics of unintentionally emergent behavior. Schmidt and O'Brien (1997) could show that the dynamics of a pendulum swinging task become unintentionally entrained and the emerging attractor states are those described by the HKB model.

Although so far only being studied in undirected tasks such as pendulum swinging, the HKB-model is a suitable model for interpersonal and emergent coordination between humans. Linking back to the aim to enable emergent human-robot interaction in activities of daily living, its two attractor states reflect the human nature to either do the same thing at the same time, or to alternately perform an action, to take turns. With regard to a pick-and-place task, in-phase relation then reflects simultaneous picking and placing, while anti-phase relation reflects alternately picking-and-placing.

Overall, due to its formal description it seems to be a good starting point for an implementable model that will allow the robot to engage in naturally emergent coordination with a human, see Chapter 7. However, as mentioned before, a pick-and-place task requires goal-directed actions. Thus, similar to the question whether humans synchronize their movements in goal-directed tasks, it is necessary to evaluate if and how a variation of the HKB-model can be utilized to enable emergent interaction between humans and robots in goal-directed actions, such as activities of daily living.

2 OBJECTIVES AND OUTLINE

Science, my boy, is made up of mistakes,
but they are mistakes which it is useful to make,
because they lead little by little to the truth.

— Jules Verne

The first objective of this work is to understand the emergence of human movement synchronization in a goal-directed repetitive task and to figure out which further principles have to be taken into consideration if we want humans also to synchronize with robots.

In order to clarify this, a setup is designed that allows for the exploration of human-human interaction as well as human-robot interaction. After an introduction to the setup and the general task, five publications are presented which add to clarify different aspects of the research question.

In the first experiment reported in Chapter 4, the purpose was to explore if movement synchronization emerges between two humans interacting in goal-directed tasks. Therefore, a goal-directed tapping task is designed with which the emergence of interaction can be studied.

With the second experiment reported in Chapter 5, human movement synchronization behavior with a non-adaptive robot is evaluated to check weather synchronization emerges naturally upon rhythmic stimulation. If synchronization emerged between a human and robot that is only repeating its behavior while displaying a human-like motion profile, that would mean that the human adapted his/her actions to the robot and human-robot movement synchronization could be established by unidirectional adaptation.

However, as results showed that the latter was not the case, Chapter 6 reports a third experiment in which it was explored if, and to what extend, mutual adaptive mechanisms and behavioral reciprocity play a role in human movement synchronization. Besides this, also the temporal dynamics of the adaptation processes are disentangled.

Once the principles of emerging movement synchronization are better understood, a model is required to describe the phenomenon and to enable the implementation on a robotic platform. As interpersonal movement synchronization can be described by use of the dynamical systems theory, Chapter 7 reports the development of a model based on coupled oscillator dynamics that capture human movement synchronization and fit the data obtained in Chapter 4. In addition, so far unpublished results from a human-robot interaction study applying the developed model are reported in Section 7.3.

However, it was shown in Chapter 6 that the synchronization process in line with the literature on event perception (see Section 1.2.2) also might be dividable into motion primitives. This is especially interesting with regard to the application of the current approach to pick-and-place tasks and to more complex tasks in general. Thus, in the final part (Chapter 8) of this work the development of a model is described which allows for human-robot interaction to emerge based on both coupled oscillator dynamics and event-based methods. Here also a first re-evaluation for human-robot interaction is provided.

The presented work will be rounded up by a discussion on further potential influencing factors to human-robot movement synchronization. Furthermore, the importance of mutual adaptation in the emergence of human-robot coordination is highlighted. Finally, chances and limitations of the current approach are considered.

3 GENERAL METHOD

The method of science is tried and true.
It is not perfect, it's just the best we have.

— Carl Sagan

For exploring the emergence of human-human coordination and its transferability to human-robot interaction as outlined in Chapter 2, an experimental setup was designed that could be used as test-bed in both HHI and HRI. Aiming for the realization of a joint ADL- or pick-and-place task, the repetitive nature of the task with regard to several objects has to be considered. Furthermore, the integration of precision demands such as when reaching for objects and placing them to a defined position, is required. However, the high-level task of setting a table also includes other features like a certain order of things and different movement directions. As the first intention in the following experiments is to explore the emergent dynamics of such a task and as differing movement trajectories could potentially also have an influence on them (see Chapter 6), the task is reduced to a goal-directed tapping task (in the following sometimes also called *target-directed*).

3.1 GENERAL EXPERIMENTAL SETUP

In all experiments outlined in the following Chapters, two humans or one human and one robot (*agents*) are sitting at the same round table (radius = 0.575 m) facing each other, see Figure 1.

On the table, four positions are marked by two blue and two red circles (radius = 0.004 m), each surrounded by a white area (radius = 0.03 m) for better visibility. The colored circles are the targets and color assigned them to one or the other agent. Both agents hold a stylus-sized object in their fist/gripper with which they had to tap the target circles. The tips of the objects were covered with felt in order to reduce tapping sounds. Besides, in all experiments agents wore stereo headphones (SONY MDR-XD200) which were used for displaying acoustic beeps as start and stop signal and additionally served to further shield tapping sounds.

Movements in the experiments in Chapters 4 to 6, are tracked and recorded by a PTI Visualeyez II VZ4000 motion tracking system (www.ptiphoenix.com). It has an online sampling rate of 30Hz used for process tracking and an offline sampling rate of 200Hz used for recording. In the experiment described in Chapter 8, a Qualisys Mo-

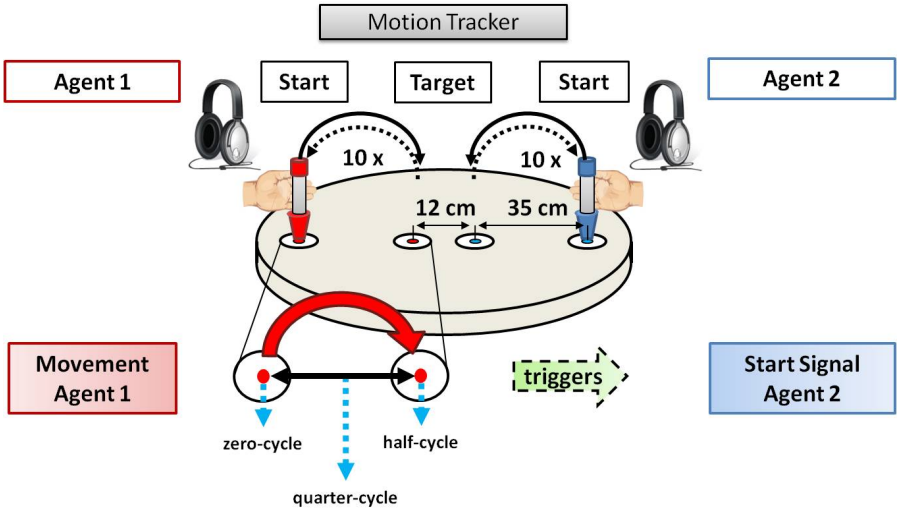

Figure 1: Experimental setup including two agents: either human-human or human-robot interaction

tion Tracking System based on Oqus4 cameras with an online tracking rate of 200Hz was employed (www.qualisys.com). Both systems use infrared light to detect markers attached to objects or bodies. We used the PTI with active markers (LEDs) and the Qualisys System with passive markers (small reflective balls) which were attached to participants hands, the objects and the robot.

This general setup was not modified throughout the first four experiments reported in the following. Only in the experiment reported in Chapter 6, an obstacle was included in the workspace of one person. Besides this, all modifications were subject to the procedure as specified in the respective methods sections. The data recorded in the first experiment (Chapter 4) was basis for the model outlined in Chapter 7. In Chapter 8, the setup was changed to allow for an evaluation of the derived model in a real pick-and-place task.

3.2 GENERAL PROCEDURE

When participants heard an auditory beep, they were instructed to immediately start tapping form the target closer to them to the target more in the center of the table and back (one cycle). These movements were to be continued until a stop signal was provided. The stop signal was given when both participants had performed at least 10 cycles each. For preventing that synchronization emerged only due to a simultaneous start of movements, different start delays were introduced in every experiment [1]:

1 Although being named differently in the following publications, e.g. zero-cycle and zero-distance determine the same start delay.

- zero-cycle (ZC)/zero-distance: both start signals were given at the same time;
- quarter-cycle (QC) /half-distance: the second agent got the start signal when the first agent was on half the way between the targets for the first time;
- half-cycle (HC)/full-distance: the second agent got the start signal when the first agent reached the target for the first time.

Besides these general elements of the procedure which were equal in all HHI or HRI experiments in the following, adaptations as to the arrangement and sequence of these conditions is outlined in the methods sections of the following Chapters.

3.3 IMPORTANT NOTES

Note that in all experiments reported in the following, participants were not instructed to move at a certain speed. Upon request, they were instructed to move at their preferred tempo. Besides, between the start and the stop signal no acoustic trigger was provided. Thus participants performed a free tapping task at their natural speed.

Also note that participants were never instructed to synchronize or to adapt to each other nor were they informed about the intention of the experiments before task completion.

3.4 ROBOTIC PLATFORM

The robot used in all following experiments is human-sized and has two anthropomorphic 7-degrees-of-freedom arms in a mirrored configuration to provide a human-like working space (Rohrmüller et al., 2010; Stanczyk, 2006), see Figure 2. However, the experiments included only movements of the robot's right arm, as also the human participants were selected to be right-handed. The arms are able to carry up to 7 kg of static load each and a wrench sensor (JR3) on its wrist. With this, an admittance-type control scheme allows the robot to realize compliant behavior of the manipulator when touching the environment.

After the wrench sensor, the robot's arms can be equipped with different end-effectors which are variable in design and functionality: For the experiments reported in Chapter 5 and the preliminary experiment reported in the discussion, the robot was equipped with a two-finger parallel gripper (*Schunk*). In the experiment described in Chapter 8 the robot's right arm was equipped with an electromagnetic gripper for enabling it to quickly grasp and release the object, see also the Paper's Appendix included in Chapter 8.

Phase estimation algorithms, algorithms for synchronization processes, the trajectory generation and the manipulator control scheme

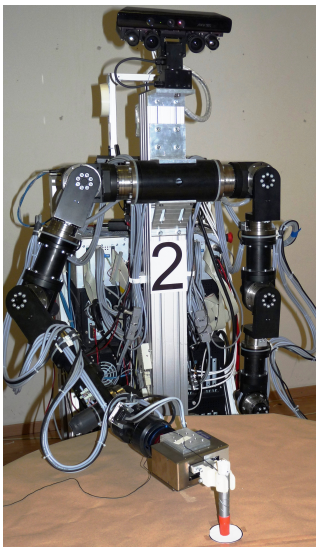

Figure 2: Human-sized robot used for the HRI experiments, here with a two-finger gripper (*Schunk*). Picture taken from Lorenz et al. (2013), © 2013, IEEE.

are developed in MATLAB/Simulink. For task execution, MATLAB Real-Time Workshop is used. The corresponding routines are executed at a sampling rate of 1 kHz on the onboard PCs of the robot. The overall processing delay between perception and action is approximately 30ms, which is the average time elapsing from marker movement until movement response of the robot (both tracking systems).

The system can be emergency-shutdown by a human via a wireless emergency button.

3.5 EVALUATION METHODS FOR MOVEMENT SYNCHRONIZATION

Considering the general concept to enable the robot to apply similar behavioral principles as humans, and that movement synchronization between humans and robots should emerge naturally, the interaction between humans and robots is evaluated with the same evaluation methods used in human interaction research. In the following a brief introduction to the data analysis methods used in the experiments reported in Chapters 4 to 7 will be provided.

The movement signals are recorded as 3D position time series. Hereof the phase $\theta_1(t)$ and $\theta_2(t)$ are derived using the Hilbert transformation as described in Chapter 7. The relative phase $\Phi(t)$ is then calculated as

$$\Phi(t) = \theta_2(t) - \theta_1(t). \tag{3}$$

One possibility of assessing movement synchronization is the cross-spectral coherence (*CSC*) [2], a measure of correlation between the two phase time series. The cross spectral coherence is derived from the circular variance (CV) of the relative phase by

$$\mathrm{CSC} = 1 - \mathrm{CV} = \left| \frac{1}{N} \sum_{j=1}^{N} e^{i\Phi(t_j)} \right|, \tag{4}$$

where N is the number of relative phase observations $\Phi(t_j)$, see also (Kreuz et al., 2007). The cross spectral coherence can vary between 0 and 1. If the relative phase is uniformly distributed, then CSC would equal 0, while a perfect synchronization would be determined by $\mathrm{CSC} = 1$.

If synchronization emerges as the product of uninstructed coordination, the entrainment between the two interacting agents is found to be weaker than in the instructed case (Schmidt and O'Brien, 1997; Schmidt and Richardson, 2008). It was observed that the phase relation is therefore not stable in the sense of a steady-state coordination, but subject to repetitive change (Fuchs and Jirsa, 2008; Schmidt and Richardson, 2008). Thus, for determining the phase relation which interacting individuals are most attracted to, the distribution of the relative phase is derived. Therefore, the observations $\Phi(t_j)$ are clustered into nine $\frac{\pi}{9} = 20°$-phase regions and accumulated over all performed trials in one condition. Depicted in a diagram in which the abscissa is clustered into phase regions and the ordinate depicts the percentage of accumulated relative phase, the *distribution of relative phase* provides an overview on how often the phase difference was for example in a phase difference of 0° and thus in an in-phase relation or 180° and thus in an anti-phase relation, see next Section.

2 The cross-spectral coherence is also called mean phase coherence or synchronization index (*SI*)

Part II

PUBLICATIONS

4

MOVEMENT SYNCHRONIZATION IN GOAL-DIRECTED TASKS

When two things
keep happening simultaneously
for an extended period of time,
the synchrony is probably not an accident.

— Steven Strogatz

4.1 SUMMARY & CONTEXT

The paper describes the planning and execution of two experiments on human-human and human robot movement synchronization.

As outlined in the introduction, human movement synchronization was so far mainly explored in undirected tasks such as pendulum swinging (Richardson et al., 2005) or rocking in chairs (Richardson et al., 2007b), finger tapping (Konvalinka et al., 2010) or postural sway (Varlet et al., 2011). This research was mainly dedicated to the temporal relation of movements.

Thus, with the first experiment in this work the intention was to explore if movement synchronization between humans emerges in tasks that share the basic features of a pick-and-place task. Pick-and-place tasks usually include carrying an object from an initial location, over a certain distance towards a target location. Thus, these tasks are goal-directed. In this work, goal-directed actions are understood as actions that are goal-directed in terms of their start and endpoint in space and that require precisely moving towards those targets in which objects are or should be located. Elsewhere, the term *goal-directed* is also utilized for higher level goals studied in terms of transitive tasks, i.e. tasks that direct towards a certain outcome. This would for example be the synchronization of movements to create harmonic music (Keller, 2008), to perform a dance (Behrends et al., 2012; Shikanai and Hachimura, 2012) or to enable team behavior in sports (Duarte et al., 2013). Also here, research aims to explore the emergent dynamics of group behavior in order to form global behavioral models or to explain the mutual dependencies between team members. However those tasks are beyond the scope of the present thesis.

Utilizing the general setup as described in Chapter 3, in the first experiment two humans were sitting at the table performing a goal-directed tapping task. Analysis of the data shows that people synchronize their movements also in those goal-directed tasks - and they

do so quickly. Furthermore it was found that people synchronize their movements both to in-phase and anti-phase relation, depending on their initial timing delay. Investigating dwell times and movement times of the segmented movement time series, it was observed that people adapt to each other to establish synchronization. It appears that if one person starts earlier than the other the dwelling phases are extended to start off simultaneously with the subsequent move and thus enable fast synchronization. However the data does not allow for a deeper investigation of adaptive mechanisms which is therefore provided in a subsequent study (see Chapter 6). Besides, the human interaction data is further analyzed in Chapter 7, where it also serves as basis for the modeling approach.

The second experiment described here is a preliminary study on human-robot movement synchronization. The same setup and procedure as for the previous HHI-experiment is utilized. Furthermore, the robot included some features from the recorded human movement data (variability, lifting height) obtained from the previous HHI experiment. Results show that there is a tendency for movement synchronization also in HRI. However, the behavior of the robot differed between participants and thus it remains unclear to which extend adaptation to the robots movements took place. Therefore, the present study is followed by a systematic investigation to explore if humans synchronize to a non-adaptive robot, see Chapter 5.

4.2 REFERENCE & CONTRIBUTION

Lorenz, T., Mörtl, A., Vlaskamp, B.N.S., Schubö, A. & Hirche, S. (2011). Synchronization in a goal-directed task: Human movement coordination with each other and robotic partners. In *20th IEEE International Symposium on Robot and Human Interactive Communication (IEEE RoMan)*, Atlanta (GA), USA, pp 198–203

Tamara Lorenz, Björn N. S. Vlaskamp, and Sandra Hirche defined the research question on synchronization in goal-directed tasks. Anna Schubö supported the research question design based on human interaction principles. Tamara Lorenz, Björn Vlaskamp and Anna Schubö designed the experiments. Tamara Lorenz and Alexander Mörtl collected the data. Tamara Lorenz and Björn Vlaskamp analyzed the data. Tamara Lorenz and Alexander Mörtl wrote the paper. Anna Schubö and Sandra Hirche supervised the project.

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Synchronization in a goal-directed task: human movement coordination with each other and robotic partners

Tamara Lorenz, Alexander Mörtl, Björn Vlaskamp, Anna Schubö, Sandra Hirche

Abstract—**Synchronization occurs frequently in human behaviour: Everybody has experienced that in a group of people walking pace tends to equalize. The phenomenon of synchrony has been established in the literature in tasks which have little in common with daily life such as pendulum swinging and chair rocking. We extend the knowledge about human movement synchronization by showing that it also occurs during goal-directed actions. In a first experiment, we investigate how synchrony emerges develops over time. In a second experiment, we show that humans also synchronize their actions with a robot. Results are interpreted in the light of joint action theory. Possible implications and improvements for human-robot interaction are discussed.**

I. INTRODUCTION

DURING human-robot interaction it is important that humans can coordinate their movements with the robot(s) in a confident and safe way. One approach to achieve this is to investigate how humans interact with each other, to extract general interaction principles from that and to implement robot behaviour in accordance with those principles [1]. However, the study of human interaction is complex and only very few interaction principles have been uncovered. In this light, an interesting phenomenon is that people tend to synchronize their actions. For example when walking in a group, people tend to synchronize gait [2]. Similar synchronization of behaviour has been observed in several circumstances and tasks such as swinging handheld pendulums [3], rocking in chairs [4] or moving one's legs [5]. Synchronization appears to be an integrated part of human interaction. It enhances perceptual sensitivity and thereby increases success in a joint action task [6]. In social psychology synchronization is furthermore acknowledged to lead to the attribution of more positive characteristics to an opponent [7] and is known to increase rapport in different situations of daily life such as teacher-student relation [8] and mother-child-bonding [9].

Synchronization seems to be an essential part of our behaviour and additionally provides a relatively easy way of describing human behaviour quantitatively. Considering that, synchronizing one's movements may provide an excellent opportunity to improve human robot interaction and thus the way robots help people achieve certain manipulations of the environment. These manipulations can involve cleaning up the house, doing the dishes or serving food. What all these tasks have in common is that they require planning and precision of movements and therefore joint action partners should be tuned to each other's movements. However, until now synchronization has only been investigated in very specific circumstances as those described above. It is thus unclear whether synchronization would occur in tasks of daily life and also the applicability of these findings for human-robot interaction remains questionable.

In the present study we asked if synchronization also occurs in a task requiring goal-directed movements. Our participants carried a pen from a start point to a target point and back again while their interaction partners were sitting at the opposite side of the table and executed the same task. The performed action bears similarities to everyday tasks that require picking or placing of objects in a shared workspace such as cleaning or setting up the table, setting up a game of chess, etc.: namely goal directed and precise movements in a shared workspace.

Additionally, we enquire if people would synchronize their movements with robots in the same task. If so, we have evidence for a general principle for interaction that is relatively easy to implement in robots and may enhance the interaction experience for the human partner.

II. METHOD

A. Participants

In total 10 dyads (13 male, 7 female) participated in the human interaction experiment (age: 18 to 28 years (M = 23.4). In the human-robot interaction experiment, six people (4 male, 2 female) participated (age: 20-28 years, M = 23). All participants were right-handed.

B. Experimental Setup

Two experiments were done: (1) human-human interaction (HHI) in which two participants were interacting with each other; (2) human-robot interaction (HRI) in which the participant was interacting with a robot. In both experiments agents were sitting at a round table (r = 0.575 m) facing each other, see Fig. 1. Four coloured dots with a diameter of 8 mm were marked at the table. Each dot was surrounded by a white area (diameter

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T. Lorenz (+49-(0)89-289-25735; tamara.lorenz@lmu.de) and B. Vlaskamp are with the Experimental Psychology Institute, Ludwig-Maximilians University, Munich, Germany.

A. Mörtl und S. Hirche are with the Institute of Automatic Control Engineering, Technische Universität München, Munich, Germany

A. Schubö is with the Psychology Section, Philipps University Marburg, Germany.

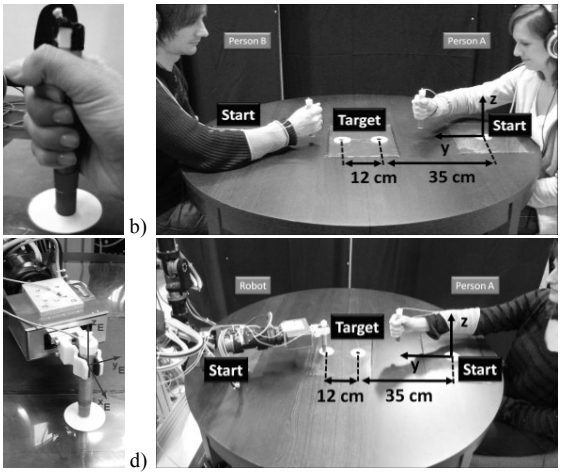

Fig. 1. Experimental setup for both experiments: a) human hand holding thepen; b) setup for human interaction (HHI) c) robotic gripper holding the pen; c) setup for human-robot interaction (HRI). LEDs for motion tracking are attached to the top of the pen.

60 mm). Agents were assigned two dots of the same colour at the respective side of the table. The dot which was located closer to the body was defined to be the start, the other the target. Participants were each equipped with a pen and instructed to grab the pen making a fist around it with their right hand. Additionally they had to wear SONY stereo headphones (MDR-XD200) with a connection to the control PC. Movements were recorded using an infrared tracking system (PTI Visualeyez II VZ4000). Wired LEDs were attached to the top of each pen and the thumb of agents' right hands/ the robot's gripper (see Fig. 1a, c). LEDs were tracked with a camera bar mounted at the ceiling. The tracking system had an online sampling rate of 30 Hz used for calculating the start signal delays in condition (2) and (3), see section II.B, and an offline sampling rate of 200 Hz used for data recording.

A. Robotic Partner

The HRI experiment was done with a human-size mobile robot with two 7 degrees-of-freedom arms [10]. We assigned a fixed position to the robot relative to the table in which it was able to reach the respective start and target areas. Motion of the robot was restricted to movements of its right arm during the experiment. In order to grasp the pen, we equipped the robot with a two-finger gripper. The robot grasped the pen in a predefined stable grasping position and did not release it during the experiment, see Fig. 1. Endpoint movement trajectories of the robot arm were composed from fifth-order polynomial segments yielding human-like minimum-jerk movements [11]. We analyzed the recorded human trajectories from the HHI experiment and reproduced the following varying features to make the movements even more human-like: variance of hitting precision in the start and target area, maximum elevation above the table including its variance and relative position between start and target area, maximum deflection from the straight line taken in the table plane, see Fig. 2. Four trajectory

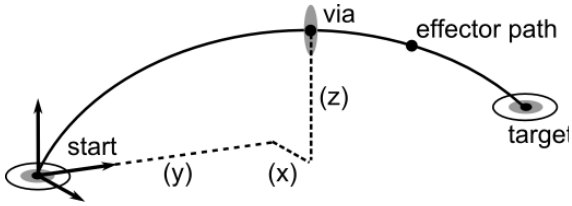

Fig. 2. Sample effector path composed by two fifth-order polynomials interpolating between start, via point and target point. The features maximum deflection in the table plane (x), relative position between start and target (y) and maximum elevation above the table (z) specify the via point. Shaded areas indicate modeled variances.

segments per movement cycle were fitted to model these features, yielding two end-points and two via-points per Cartesian direction respectively. The robot's arm trajectory was composed by interpolation of two fifth order polynomials, one between start- and via-point, the other from via- to target-point and reverse. Interpolation was done separately in the three Cartesian directions similar to Huber et al. [12]. The orientation of the robot arm was commanded such that the z_E-axis of the arm's endpoint always pointed upwards normal to the table plane (see Fig. 1c). The grippers orientation angle around the z_E-axis had to be changed between start and target area to fit the workspace limitations of the robot arm. Due to technical and safety reasons the per-cycle frequency of the robot's movements was set to 0.56 Hz.

B. Task and Procedure

Participants were instructed to rest in the starting position with their pen upwards until they heard an acoustic signal through their headphones. This was the signal to start moving the pen from their individual start position to the respective target position, tap on the dot, move back and tap on the start position. Moving forward, tapping, moving backward and tapping again was defined as one cycle. Cycles were to be repeated until a second acoustic signal was presented which was automatically triggered when both agents had performed at least 10 cycles. Note that participants were naïve as to the goal of the experiment and were not instructed to adapt their movements to each other.

When people are working together in daily life they might not start their tasks in sync. One of the agents might already have preceded a certain part of the required trajectory before the second agent starts to move. To emulate these circumstances, different timings of start signals were given. In both experiments (HHI/HRI) three different start conditions were introduced: (1) zero-distance: the start signal was presented at the same time for both participants; (2) half-distance: the start signal for the second person was presented when the first person passed half the way to the target; (3) full-distance: the start signal for the second person was presented when the first person had reached the target.

Both experiments were performed in six sets which consisted of six trials with equal start condition. This led to a total of 12 repetitions for each condition. During the conditions (2) and (3) the first start signal was assigned

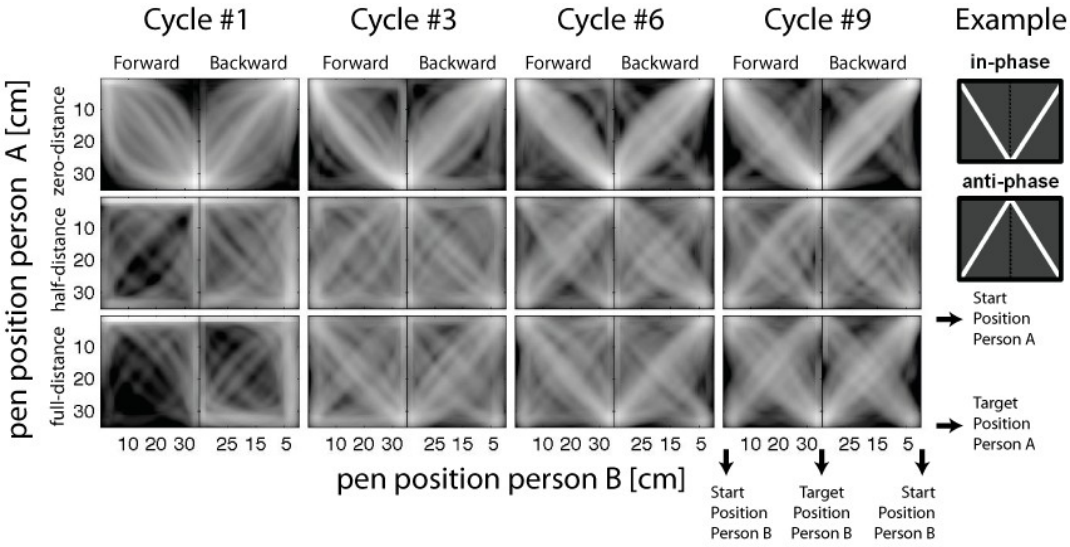

Fig. 3. Frequency distribution of relative movement data in action direction (y) for the conditions zero-distance (upper panels), half-distance (middle panels) and full-distance (lower panels); forward and backward movements are plotted separately for cycle number 1,3,6 and 9; the bright lines show the frequency of the relative position of person B (ordinate) towards A (abscissa); in the zero-distance condition the lines become straighter which shows that the frequency of being at the same place at the same time (in-phase) is increasing towards the 9th cycle; this indicates that people are in fact adapting their movements to each other. For half-distance and full-distance it can additionally be observed that the interaction partner is at the opposite place at the same time (anti-phase), which is more expressed if people start with full-distance and in general later than in the zero-distance condition; in the upper right an example of perfect in-phase/anti-phase relation is given.

randomly to one of both participants and counterbalanced in each set. Note that the task did not require synchronization which allowed us to explore if it emerges naturally.

C. Data Analysis

Movement data of both experiments were processed in the same way: velocity was calculated from the Euclidian distance between data points in Cartesian coordinates. A fourth order low-pass Butterworth filter with a cut-off frequency of 10 Hz was applied. The resulting phase shift was corrected by applying the same filter reversely. Every time the velocity-time profile had a minimum, a pen tapping was assumed. Herewith the data was divided into 10 cycles. Due to variations in trial terminations, the 10th cycle was excluded from analysis.

Using one of the methods tested by Teasdale et al. [13], movement onset was calculated as the first time the movement crossed 15% of the peak acceleration of the trial.

III. Results

A. Human-Human Interaction

First, we looked at the relative positions of the dyads' hands. From literature it is known that during human synchronization of movements mainly two dominant states emerge: in-phase, i.e. agents execute the same part of the movement at the same time, or anti-phase, i.e. agents execute the opposite part of the movement at the same time [14]. In order to find out whether and how often a similar relation occurred in our experiment, we plotted a frequency distribution of all the movement data of person A as a function of the movement data of person B. For trials and cycles the y-position of person A was plotted as a function of person B's y-position, see also Fig. 2. The resulting curve was sampled with an underlying grid of 100 x 100 cells and the number of times each cell in the grid was hit by a curve was determined. Resulting frequencies were plotted as a heat map in which brightness codes frequency, see Fig. 3. In these plots, perfect synchrony appears as straight lines. When the participants are perfectly in-phase during forward movement, a line goes from top left to bottom right. During backwards movements - where the abscissa labelling goes down again, the plot shows a straight line from the bottom left to the top right. In perfect anti-phase the pattern is mirrored. When participants are out of sync, data appear curved. Going from left to right in Fig. 3, we can see that during the first cycle the data tend to be curved. This is particularly true in the half-distance and full-distance conditions. Here behaviour is very idiosyncratic, because very few straight lines become apparent. After cycle 1, people quickly adapt and by the time they enter cycle 3, there are still curved lines, but straight lines have become more prevalent with possibly slightly more lines indicating in-phase movements. Hence, after only three cycles synchronization is established.

To scrutinize synchronization further, we analyzed the lag between the actions of each dyad, i.e. the between-dyad time difference in the execution of movements. We operationalize synchrony as the degree to which lag varies over time: the less lag varies, the more the actions are synchronized. Note that this means that also actions that are not executed at the same time can be executed synchronously. We calculated lag at several reference points within the action cycles: the target area entry, target area exit, start area entry, start area exit. Lag variability is calculated as the absolute difference at the

reference point between two subsequent cycles. Because some cycles are executed faster than others we normalized lag to each cycle's duration (calculated as the average of both participants). In Fig. 4, lag variability is plotted as a function of the cycle difference for which it is calculated. The plotted value is the across-subject mean of within-subject median lag variability. The reference point for this figure was target area entry. Clearly, lag variability goes down as the task proceeds, $F(7,63) = 31.99$, $p < .001$. Contrasts reveal that the first, $F(1,9) = 58.03$, $p < .001$, and the second lag variability, $F(1,8) = 19.72$, $p < .01$, are significantly higher than the eighth, indicating that lag variability between time points in which people enter the target area is decreasing in the first cycles. No differences were observed for all other levels, all $p > .1$. We confirmed this finding by measuring lag variability at other reference points as well (target area exit, start area entry, start area exit) with similar results. So, clearly people adjusted their behaviour towards synchronized movements and they did so mostly in the beginning.

Since synchronization measured by lag variability occurred more often as more cycles had been executed, participants adapted their behaviour. Here different strategies could have been applied: participants could either have changed how long they dwelled in the start and target area, or they could have changed the speed at which they performed the movements and thus the movement time for this segment. Therefore we calculated dwell times and movement times and determined the difference regarding these measures between interaction partners. Because we know that synchronization improves over time, we expect either one of these measures or both to go down. Fig. 5 shows the dwell time differences in target and start area and forward/backward movement time differences between participants. A significant effect for cycle number was found for between-subject movement time differences during forward movements, $F(8,72) = 4.31$, $p < .001$. Contrasts show that movement

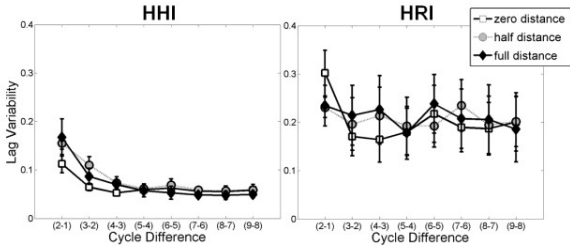

Fig. 4. Lag variability at target area entry between agents for human interaction (left panel) and human-robot interaction (right panel). The left panel shows that people adapt their movements towards a more stable pattern.

time differences were higher during the first forward movement compared to the last, $F(1,9) = 10.05$, $p < 0.05$, whereas no differences were observed for the other levels, all $p > .09$. During backwards movements, no differences were observed, $p > .6$. So, only forward movement time differences seem to contribute substantially to synchronization.

Looking at differences in dwell times in the target area, there was a significant main effect for cycles, $F(8,72) = 12.70$, $p < .001$. Contrasts show that the difference in time spent in the target area during the first cycle was higher than in the last, $F(1,9) = 17.00$, $p < .01$. Also during the second cycle dwell time differences in the target area were higher than in the last cycle, $F(1,9) = 5.10$, $p = 0.05$. For the other cycles no differences in dwell time were observed compared to the last cycle, all $p > .3$. Dwell time differences in the start area also showed a main effect of cycle $F(8,72) = 4.65$, $p < .001$. Contrasts reveal a difference between the first and the last cycle, $F(1,9) = 16.87$, $p < .01$. For all other cycles no differences were found to the last one, all $p > .1$. Regarding the factor condition, no effect was observed for all comparisons, $p > .1$. Also no interaction effects were observed, $p > .1$. In short, dwell times convincingly reflect synchronization in the course of a trial.

We also had a look on the average frequency with which the human movements were executed. Taking the

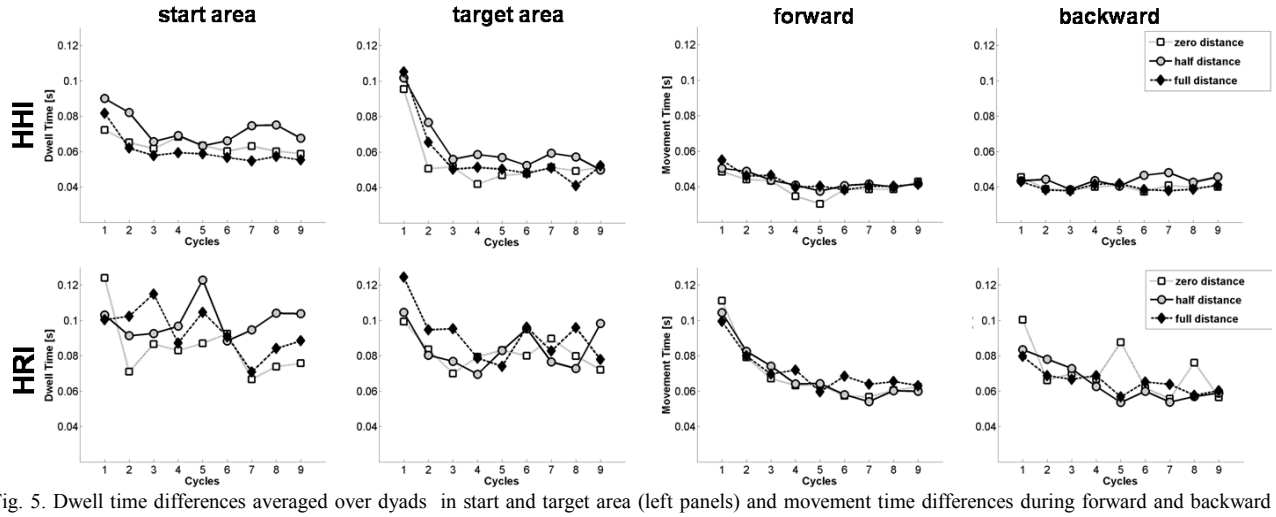

Fig. 5. Dwell time differences averaged over dyads in start and target area (left panels) and movement time differences during forward and backward movements (right panels); upper graphs show the data obtained from the human interaction experiment; lower graphs data from the human-robot interaction task;

mean over all participants we found that humans performed with a frequency of 0.73 Hz.

B. Human-Robot Interaction

Now that we found synchronization in goal-directed human-human interaction tasks, an interesting question is whether this phenomenon also occurs in human-robot interaction. In order to determine this, we applied identical measures used for analyzing the HHI experiment to analyze human-robot interaction.

During HRI, two participants were roughly moving at twice the rate of the maximal robot frequency of 0.56 Hz throughout the whole session. Although they were possibly adapting to the robot using a 2:1 rhythm, their data was not included into statistical analysis. From the remaining data 22 trials had to be excluded due to sensor malfunction. They were roughly equally distributed over conditions. Note that due to the small sample size, there may not be enough statistical power to reveal effects yet.

Nevertheless, we found initial evidence for synchronization. For the forward movement a main effect of movement time difference was found over cycles, $F(8,24) = 11.86$, $p < .001$. Contrasts reveal a difference between the first and the last cycle, $F(1,3) = 37.67$, $p < 0.01$, and between the third and the last cycle $F(1,3) = 11.14$, $p < 0.05$. During backwards movement there is also a main effect of cycles, $F(8,24) = 3.81$, $p < 0.01$, with a significant difference between the first and the last, $F(1,3) = 10.98$, $p < 0.05$, and the third and the last cycle, $F(1,3) = 11.41$, $p < 0.05$. Dwell time differences didn't show a main effect for the factor cycles in neither the target area, $p > .4$, nor the start area $p > .2$. Similar to the human interaction data, within all comparisons we didn't find any significant effect for the factor condition, all $p > .4$, nor any significant interaction effect, all $p > .1$. Watching Fig. 4, a decrease in lag variability of entry to target area across cycle differences seems evident; however there was no statistical effect, $p > .2$.

IV. Discussion

It is known that people tend to synchronize their movements in simple rhythmical and repetitive tasks like pendulum swinging [3], or rocking in chairs [4]. With the study at hand we answer the question if people also synchronize their movements in a goal-directed task. Our findings suggest that they do so and they do so quickly.

A. Human Synchronization Strategy in a Goal-Directed Task

In our HHI experiment, the results between conditions are very similar, but certainly the frequency distributions indicate that there are some differences.

Firstly, if people started moving at zero-distance they showed a clear tendency towards a stable synchronization pattern. The more cycles were performed, the more people were at the same time in the same part of their movement.

Secondly, in the full-distance and in the half-distance condition we see that in most trials stable synchronization is achieved, but this pattern is established later than in the zero-distance condition.

Thirdly, in the full-distance condition anti-phase and in-phase relationships occur roughly equally often which was also frequently observed in the half-distance condition. One might have expected that if zero-distance mainly leads to an in-phase relation, full-distance would mainly lead to an anti-phase relation. Altogether these results show that people synchronize their movements in goal directed tasks and it also shows that the movements are continuously adapted.

In the study of Richardson et al. [4] people were instructed to start moving at different times and it was found that during a non-goal directed task like rocking in chairs people nevertheless mainly exhibit in-phase relation independent from the temporal difference with which they started moving. It was argued that for the unintentional synchronization during rocking, the attractor anti-phase was too weak to sustain any significant coordination. In contrast, our results suggest that in a goal-directed task anti-phase is a frequently appearing attractor. It is possible that agents chose the attractor that is closest. For example it might be that in some cases the movement of the first person was performed like a single action because the workspace was still empty. If so then it would be performed slower than in joint action. Next, when the second person started moving, he/she entered a joint action task and may apply strategies other than those of the first person like leaving the target area more quickly [15]. The single action of one person in relation to the joint action strategy of the other person could lead to a decreased time difference which results again in an in-phase relation as this is the closer attractor, so to say. Alternatively it could be that precisely hitting the target and the start point had a higher priority than synchronization because the latter was not required nor instructed. Only in cases in which an attractor was already close, synchronization was aspired over time.

In order to find out how adaptation emerges, we looked at the differences of dwell time in the target and start area and at the differences of movement time for the forward and backward movement. For the first forward movement we found a significantly larger temporal difference between interaction partners than in all other cycles. It seems plausible that in an interaction situation people slow down to see what the other person does. As gaze tends to precede manual movements [16] it would be easy to quickly glance at the activity of the other agent during forward movements (because the agents were sitting opposite of each other). By slowing down, resources could be freed-up and the own and the other's movement could be judged [17]. This seems especially plausible because no changes in movement time difference were found for the backwards movement.

Similar results were obtained for the difference in dwell time in the start and in the target area. During the first cycles the dwell time differences in target and start areas

were higher than during the other cycles. This higher dwell time difference may indicate that one agent was waiting for the other agent. Once both agents are located in the same place, synchronous behaviour can easily be established by starting off synchronously again. That establishing the pattern seemed to take a bit longer for the full-distance condition might be due to the fact that the movement is harder to start off simultaneously from defined positions if these are further apart in space, namely one person rests in the target area while the other one rests in the start area.

The fact that no differences between conditions were found shows that the strategies applied to establish coordination are the same regardless of how the movement is started.

B. Human Synchronization Strategy in a Goal-Directed Task with a Robot

The second experiment provides a first insight into synchronization of human movements to a robot. On the basis of the present set of data which involved four human-robot dyads, there are already signs that synchronization occurs. The data generally show a similar pattern like that of human interaction. Synchronization can be assumed because especially for zero-distance the lag variability for the first cycle difference is about one half higher than the others. This is remarkable because the robot was moving about a third slower than humans on average did during HHI. That could potentially have made it more difficult to synchronize and the relative high lag variability compared to the HHI condition may be related to this. Nevertheless, apart from two dyads which might also have adapted in another rhythm, i.e. 2:1, we find that people adapted to the robot. Thus, they slowed down in order to synchronize with the robot.

Additionally, average movement time difference between the human agents and the robot for the forward movements were higher in the first three cycles. If it is true what was discussed for human interaction, namely that the reactions of the interaction partner are judged and integrated during the first forward movement, then here the judgement of the robot's movements may have required more time. It is also possible that humans tried to "encourage" the robot to follow their movements which caused a greater lag. And although the robot might not have reacted in the expected way, synchronization still appeared. This is especially remarkable because adaptation to the interaction partner was possible, but not required to fulfil the task.

V. CONCLUSION

In the study at hand we investigated synchronization of movements between two agents. Synchronization has been studied in various scenarios (chair rocking, pendulum swinging) but not in tasks that relate to daily life. For our study we therefore included one key aspect of tasks that people often do together, namely that they require goal-directed movements. We showed that also under these constraints synchronization occurred. Considering our results we provide evidence that synchronization may occur in a wide range of everyday tasks. Furthermore we found, that people also apply the same strategies when interacting with a robot. This is a useful finding for human-centred robotics because synchronization principles are relatively easy to implement and might therefore be a reasonable step towards predictable and safe human-robot interaction.

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5 NON-ADAPTIVE HUMAN-ROBOT INTERACTION

Man is a creature that can get used to anything,
and I think that is the best definition of him.

— Fyodor Dostoyevsky

5.1 SUMMARY & CONTEXT

This short paper reports an experiment which explores if movement synchronization naturally emerges between a human and a non-adaptive robot in a goal-directed task. If synchronization between the human and the robot emerges in such a scenario, the human would have adapted his/her movements to those of the robot in space and time automatically without being instructed to do so.

Utilizing again the same setup and procedure as described in Chapter 3, a human was performing the goal-directed tapping task together with a non-adaptive robot which moved at the mean human tapping frequency identified in Chapter 4.

Results show that humans do not synchronize to a non-adaptive robot in the goal-directed task. If they start-off at the same time as the robot, in-phase synchronization is obtained. However it can not be excluded that this only reflects the maintaining of the own starting speed. If human and robot start with a delay, this delay is also maintained and synchronization does not emerge in the same way as it does in HHI for the same setting. Surprisingly, the distribution of relative phase shows a peak in the 90° phase region which is assumed to be the most unstable state in interpersonal coordination (Wilson et al., 2005). In fact, this might also be owed to merely maintaining the introduced delay. Nevertheless also other explanations are possible. Due to page limits, only a brief discussion on the possible reasons for this result is given in this short report. A deeper reasoning on why synchronization between humans and robots may not arise in this case and how the results can be further interpreted is therefore provided in the general discussion, Chapter 9.

Considering the literature on human interaction, it appears that the emergence of coordination depends on the *mutual* correction of timing errors or phase Section 1.2. Thus, in the present case, humans might even have tried to adapt their behavior, but as no reaction was perceived from the robot, the full adaptation effort would only be taken on purpose, i.e. if it is instructed or leads to an outcome. This notion was already theoretically proposed in Marin et al. (2009), however not tested. Besides, although lots of work has been dedicated

to the exploration of human adaptation mechanisms in undirected tasks (Repp, 2005; Repp et al., 2012), human movement adaptation in goal-directed synchronization will be explored in more detail in Chapter 6.

5.2 REFERENCE & CONTRIBUTION

Lorenz, T., Mörtl, A., & Hirche, S. (2013). Movement synchronization fails during non-adaptive human-robot interaction. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, Tokyo, Japan, pp. 189–190

Tamara Lorenz, Alexander Mörtl and Sandra Hirche defined the research question on non-adaptive Human-Robot movement synchronization. Tamara Lorenz and Alexander Mörtl conducted the experiment. Tamara Lorenz analyzed the data with support by Alexander Mörtl. Tamara Lorenz wrote the paper with comments of Alexander Mörtl and Sandra Hirche. Sandra Hirche supervised the project.

Movement Synchronization Fails during Non-Adaptive Human-Robot Interaction

Tamara Lorenz
Experimental Psychology
Ludwig-Maximilians Universität (LMU)
Munich, Germany
tamara.lorenz@lmu.de

Alexander Mörtl, Sandra Hirche
Institute of Automatic Control Engineering
Technische Universität München (TUM)
Munich, Germany
{moertl, hirche}@tum.de

***Abstract*—Interpersonal movement synchronization is a phenomenon that does not only increase the predictability of movements; it also increases rapport among people. In this line, synchronization might enhance human-robot interaction. An experiment is presented which explores to what extend a human synchronizes own movements to a non-adaptive robot during a repetitive tapping task. It is shown that the human does not take over the complete effort of movement adaptation to reach synchronization, which indicates the need for adaptive robots.**

Keywords—Movement synchronization; adaptation; repetitive actions; human-robot interaction;

I. INTRODUCTION

Humans synchronize their movements in many different ways during their daily activities. When talking to each other, they adapt their postural sway [1] and when walking next to each other they synchronize their gait [2]. But synchronization is more. Valdesolo et al. [3] showed that movement synchronization enhances the perceptual sensitivity among agents which potentially enhances their ability to pursue joint goals. Besides that, synchronization also seems to serve a social purpose: it creates rapport and altruism among people [4, 5]. Thus, movement synchronization is a fundamental principle for human motor coordination and social interaction.

Marin et al. [6] suggest that movement synchronization could also serve as a key element for the naturalness of human-like social interactions with robots. However, if synchronization should serve in a meaningful human-robot interaction, further questions have to be investigated. In our previous study [7] we observed that humans not only synchronize purely repetitive movements, they also synchronize when these movements are goal-directed. This is important when for example thinking about joint human-robot pick-and-place tasks.

Another interesting question in this context is, whether movement synchronization is a bidirectional phenomenon, and thus, only occurs if both agents (human and robot) attempt to synchronize or if synchronization is that "important" during repetitive interaction tasks, that the human takes over the complete adaptation effort.

With the study presented in this report we therefore explore the question whether humans synchronize their movements to a non-adaptive robot during a repetitive goal-directed tapping task.

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II. METHOD

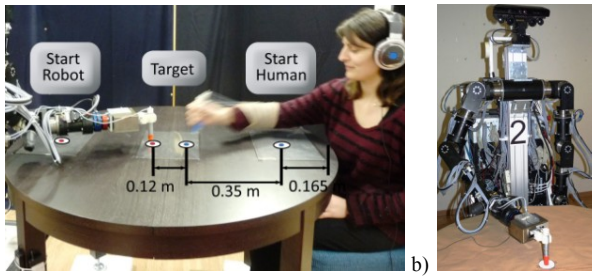
To explore whether a human would take over the complete adaptation effort in order to synchronize to a non-adaptive robot, we modified the experimental paradigm introduced in [7]. Human and robot were sitting vis-à-vis on a round table holding a pen in their right hand and gripper. LED-markers for motion tracking (*PTI-Phoenix*) were attached to the end of the pens. The human was wearing stereo headphones. On the table, four colored dots were marked which are defined to be start and target for each agent respectively, see Figure 1a. In total, 4 male and 4 female, average age 28.8 years, took part in the experiment.

A. Task and procedure

Both actors' task was to grasp the pen, and orthogonally place it in the start position on the table. When the start signal was provided (auditory via headphone for the human), the pen was to be lifted and positioned in the target position and back again to the start position. These movement cycles were to be continued until an auditory stop signal was provided. Three start signal delays were introduced and balanced over trials: zero-cycle (ZC, both agents start simultaneously), quarter-cycle (QC, the 2nd agent starts when the 1st agent passed half the way to the target) and half-cycle (HC, the 2nd agent starts when the 1st agent reached the target).

B. Robot

A human-size mobile robot equipped with a pair of seven degrees-of-freedom arms [8] was used for the experiment, see Figure 1b. Details on the robot's system can be found in [9], [10]. For grasping the pen, the robot's arm is equipped with a two-finger parallel gripper *(Schunk)*. At the beginning of the



a) b)

Figure 1. a) Experimental setup; b) Robot.

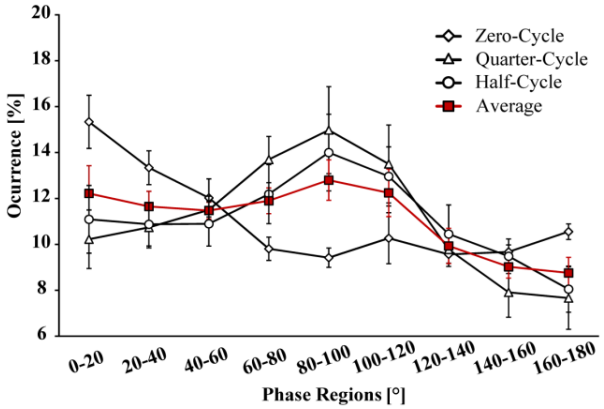


Figure 2. Distribution of relative phase

experiment, the robot grasps the pen once in a predefined rigid grasping position. Using an admittance-type control scheme based on a wrench sensor *(JR3)* in the robot's wrist, compliant behavior of the arm is realized when touching the table in the tapping areas. Movements between the tapping points are generated by minimum-jerk profiles at a constant frequency.

III. Results and Discussion

In line with [11, 12], the relative phase difference between movement signals was calculated per trial and averaged for each start condition respectively. If in-phase synchronization occurred, a peak for data in the 0-20° region should be found, for anti-phase synchronization in the 160-180° region.

To access whether there was a difference in the phase regions, a 3 x 9 repeated measures ANOVA was performed with the within subject factors *start* (ZC, QC, HC) and *phase region* (0°-180°). A significant main effect was found for phase region, $F(8,56) = 3.23$, $p < .01$, see average curve in Figure 2. Post hoc contrasts show that this difference derives from a lower frequency of occurrence in the regions ranging from 120° to 180°. However, no peak for neither in-phase nor anti-phase synchronization can be found. The interaction also reached significance indicating a difference in the distribution of relative phase after different start delays, $F(16,112) = 3.36$, $p < .001$. Looking at the distribution after ZC delay in Figure 2, a peak at the 0-20° phase region can be observed. However, as human and robot had to start off at the same time in this condition, no delay was triggered and the human could move with no phase delay to the robot just by maintaining the original speed – and without synchronizing to the robot. After starting off with a QC or HC delay, no peak for in-phase or anti-phase synchronization can be observed. Post hoc observations show that the interaction derives from the higher percentage in the phase region 80-100° for the QC condition. During this condition, participants and the robot were triggered to start moving when the respective other was on half his way to the target. Thus, when performing in a constant velocity without adapting to the movements of one another, a phase shift of about 90° seems reasonable.

Summing up it was found, that with a non-adaptive robot, synchronization does not emerge naturally like it would during the interaction of two humans in a similar task (see [7], [11]). This is in line with a suggestion of [6], claiming that if the robot never changes its behavior, this could be uncomfortable and the human would stop adapting his/her behavior. Yet the question remains if robotic adaptation encourages humans to adapt to robotic movements during goal-directed tasks (bidirectonality) and if adaptive robotic movements would lead to successful human-robot movement synchronization and a subjectively pleasant sense of interaction.

IV. Conclusion and Outlook

With the work at hand it was shown that people do not synchronize to a robot in a repetitive, goal-directed task if the robot is non-adaptive. As a next step, an exploration of the appropriate adaptation would be required. The synchronization model presented in [11] has to be implemented onto a robotic platform which will allow to test human-robot synchronization behavior.

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6

EXPLORING HUMAN ADAPTATION IN A GOAL-DIRECTED SYNCHRONIZATION TASK

We first make our habits,
then our habits make us.

— John Dryden

6.1 SUMMARY & CONTEXT

Resulting form the previous study on movement synchronization with non-adaptive robots it was hypothesized that a mutual adaptation is required for movement synchronization to emerge naturally. Besides, although lots of work has been dedicated to the exploration of human adaptation mechanisms in undirected tasks (Repp, 2005; Repp et al., 2012), human movement adaptation in goal-directed synchronization is so far not considered. However, if adaptive robots should be created that interact with humans in goal-directed actions, a deeper understanding of human adaptation mechanisms in this area is required.

In the current experiment, the setup outlined in Chapter 3 was slightly modified. In 50 % of the trials a vertical obstacle was positioned to the workspace of one person (hampered person). Thus, in order to clear the obstacle and reach for the target circle, this person had to extend the movement trajectory compared to the trajectory in the situation in which no obstacle is present (incongruent vs. congruent configuration). The other person did not have to overcome an obstacle and was thus free to move over the whole course of the experiment (free person). The extension of the trajectory requires an extra adaptation of one or both interaction partners if synchronous behavior is still emerging and therefore allows for the exploration of the underlying adaptation strategy.

To control whether the adaptation was indeed a result of adaptation and not induced by start triggers, each person's movement data was also related to the movement data of the participants he/she did not interact with. In this case, no movement synchronization was found. If however people were interacting and had the possibility to adapt their behavior to each other, movement synchronization still emerges despite the presence of the obstacle.

A segmentation of the movement data allowed for a deeper investigation of the adaptation behavior itself. It was found that in response to the forced trajectory extension, the hampered person increased movement velocity and at the same time decreased dwell times in the

targets. The free person, who's trajectory was not directly affected by the obstacle, actually also adapted to the new situation. Despite his/her trajectory was marginally extended in the incongruent configuration, the free person actually increased dwell times while keeping the movement velocity similar to the congruent configuration. Thus, while the hampered person adapted by being faster, the free person waited for the interaction partner while at the same time making oneself as predictable as possible.

Results are discussed with respect to joint action and event perception theories, obstacle avoidance behavior and possible movement interference.

Overall, if an obstacle is added to a target-directed tapping task in a shared workspace, movement synchronization between two persons not only emerges; it also requires complementary actions like any higher level joint action task. Thus, if human-robot interaction should benefit from movement synchronization with a human, the robot not only needs to be adaptive, it also needs to be able to adapt its behavior in different segments of the movement time series (dwell time/ movement time).

Note: In the following publication, *goal*-directed tapping is termed *target*-directed tapping. Here *target* refers to the marked positions on the table which participants had to tap between.

6.2 REFERENCE & CONTRIBUTION

Lorenz, T., Vlaskamp, B. N. S., Kasparbauer, A.-M., Mörtl, A., & Hirche, S. (2014). Dyadic movement synchronization while performing incongruent trajectories requires mutual adaptation. In *Frontiers in Human Neuroscience*, 8, pp 461. doi:10.3389/fnhum.2014.00461

Tamara Lorenz, Björn Vlaskamp, and Sandra Hirche defined the research question on synchronization in goal-directed tasks. Tamara Lorenz, Björn Vlaskamp, and Anna-Maria Kasparbauer designed the experiment. Anna-Maria Kasparbauer, Tamara Lorenz, and Alexander Mörtl performed the experiment. Tamara Lorenz, Anna-Maria Kasparbauer, Björn Vlaskamp, and Alexander Mörtl analyzed the data. Tamara Lorenz, Anna-Maria Kasparbauer, Björn Vlaskamp, Alexander Mörtl, and Sandra Hirche wrote the paper. Björn Vlaskamp and Sandra Hirche supervised the project.

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Dyadic movement synchronization while performing incongruent trajectories requires mutual adaptation

Tamara Lorenz[1,2]*, Björn N. S. Vlaskamp[1,3], Anna-Maria Kasparbauer[1,4], Alexander Mörtl[2] and Sandra Hirche[2]

[1] Experimental Psychology, Ludwig-Maximilians University, Munich, Germany
[2] Institute for Information-Oriented Control, Technische Universität München, Munich, Germany
[3] Philips Research, Eindhoven, Netherlands
[4] Institute of Psychology, Rheinische Friedrich-Wilhelms Universität, Bonn, Germany

Edited by:
Sven Bestmann, University College London, UK

Reviewed by:
Arun Bokde, Trinity College Dublin, Ireland
James Kilner, University College London, UK

***Correspondence:**
Tamara Lorenz, Technische Universität München, Institute for Information-Oriented Control, Barerstr. 21, 80801 Munich, Germany
e-mail: t.lorenz@tum.de

Unintentional movement synchronization is often emerging between interacting humans. In the present study, we investigate the extent to which the incongruence of movement trajectories has an influence on unintentional dyadic movement synchronization. During a target-directed tapping task, a participant repetitively moved between two targets in front of another participant who performed the same task in parallel but independently. When the movement path of one participant was changed by placing an obstacle between the targets, the degree of their unintentional movement synchronization was measured. Movement synchronization was observed despite of their substantially different movement trajectories. A deeper investigation of the participant's unintentional behavior shows, that although the actor who cleared the obstacle puts unintentional effort in establishing synchrony by increasing movement velocity—the other actor also unintentionally adjusted his/her behavior by increasing dwell times. Results are discussed in the light of joint action, movement interference and obstacle avoidance behavior.

Keywords: joint action, movement synchronization, obstacle avoidance, movement interference, movement coordination, action timing

INTRODUCTION

Synchronization is a phenomenon which naturally emerges across species and systems (Strogatz, 2003). Between humans, almost everybody has experienced that when walking next to another person, one automatically synchronizes walking pace (van Ulzen et al., 2008; Nessler and Gilliland, 2009). Interestingly, people synchronize their movements as soon as they exchange sensory information (Issartel et al., 2007) and it seems that if visual information on the other's movements is available, synchronization is inevitable (Schmidt and O'Brien, 1997). Previously, synchronization was studied in numerous tasks like for example tapping (Schöner et al., 1986; Konvalinka et al., 2010), pendulum swinging (Richardson et al., 2008), walking (Nessler and Gilliland, 2009), rocking in chairs (Richardson et al., 2007) or drumming (Kirschner and Tomasello, 2009). These studies showed that people tend to adapt to each other and synchronize their movements to either an in-phase relation (being at the same stage of the movement at the same time) or an anti-phase relation (being at the opposite stage of the movement at the same time).

Yet little is known about the requirements for movement synchronization to occur. Interaction partners need to be able to make movements producing equal rhythm, which requires similar temporal and spatial abilities. However, there may be more subtle complications. If humans act alone, their movements are believed to follow certain efficiency criteria such as minimization of movement time or required energy (Engelbrecht, 2001) [although principles of motor control are not completely understood yet (Latash et al., 2010)]. Accordingly, one would expect these efficiency criteria to be a necessary requirement during interaction, and thus also for movement synchronization. Therefore it is remarkable that interpersonal synchronization is even established if the individual's minimization criterion is violated. One example is provided by Richardson et al. (2007) who had participants rocking in chairs at their own preferred rate. When their chairs were manipulated to have differing natural frequencies, the coherence—as a measure of entrainment or coupling strength—was decreased compared to the case when both participants were rocking in chairs with the same natural frequencies. This potentially resulted from the higher effort to maintain a phase-locked frequency relation if the natural frequencies of the systems differ. But although the required energy was higher for one person, synchronization still emerged unintentionally.

However, Richardson et al. only manipulated the natural frequencies of the chairs, while the temporal and spatial constraints were still equal for both participants: people were rocking in identical chairs. Thus, the trajectories performed while rocking were still the same. Here, a particularly interesting—and so far untested—situation arises: does unintentional synchronization still emerge when movement trajectories are different?

If synchronization emerges in such a situation, this requires an unintentional adjustment of movements from at least one person. With this however, additional complications arise: it is known that when people watch movements different to those performed by themselves (incongruent behavior), a so called *interference*

effect can be observed (Brass et al., 2001; Kilner et al., 2003; Sebanz et al., 2003; Stanley et al., 2007). The interference effect increases movement onset and reaction times in response to spatial incompatibility (Brass et al., 2001; Sebanz et al., 2003), but it also affects movement trajectories (Kilner et al., 2003; Stanley et al., 2007). It is suggested that while performing the own action, a simultaneous activation of the human equivalent to the mirror neuron system (Rizzolatti et al., 1996; Rizzolatti, 2005) causes some kind of *motor contagion* (Blakemore and Frith, 2005). By observing somebody else's action and activating one's representation of it, the own action is facilitated. However if the observed action does not match the representation of the own executed movements, this might create additional load as incorrect motor programs have to be inhibited. For the actual execution of movement this means that people tend to unintentionally mirror the movements they see, while they actually intentionally try to perform a different movement. This conflict is hypothesized to cause the deviation. Nevertheless, visual information exchange was also found to be crucial for unintentional synchronization to occur (see Richardson et al., 2005). Thus, in a situation in which trajectories are incongruent and may interfere due to visual information exchange, an interesting question is whether movement synchronization would still emerge.

In order to answer this question we introduce a study in which participants performed repetitive target-directed arm movements. From previous work it is known that in these tasks, movement synchronization occurs rapidly when participants can make congruent movements (Lorenz et al., 2011; Mörtl et al., 2012). Thus, for the study at hand we exploit a similar experimental setup. An obstacle is put in one participant's way—which causes an adjustment of movement trajectories for the actor who has to move around it.

Obstacle avoidance as a single action is characterized by deviations which cause increased movement times or a decrease in movement speed respectively (Tipper et al., 1997; Coppard et al., 2001; Castiello, 2003; Chapman and Goodale, 2008; Menger et al., 2012). During joint action this can also have implications for synchronization. If one actor has to move around an obstacle, movements become incongruent in space and might therefore also be incongruent in time. Therefore, in this study we ask whether synchronization still emerges if movement trajectories of two individuals are incongruent in space and therefore also do not match in time—and which strategies are applied to establish it.

MATERIALS AND METHODS

In order to access participants' movement synchronization behavior during incongruent conditions, a dyadic target-directed tapping-task was developed in which one participant had to clear an obstacle, which enforces the performance of a different trajectory. The experiment was approved by the ethics committee of the faculty for psychology and pedagogics of the LMU and conducted in accordance with the Declaration of Helsinki.

PARTICIPANTS

Ten dyads (20 people, 7 female) took part in the experiment. Their age ranged from 21 to 45 years ($M = 26.6$ years). Participants were recruited from a local (LMU Munich) participant database and paid 8 Euro/hour for participation. All participants were right handed and had normal or corrected to normal vision. Prior to the experiment, all participants were provided with written instructions and signed written consent.

EXPERIMENTAL SETUP

Each dyad sat at a round table (radius = 0.575 m) facing each other, see **Figure 1**. Four colored target cycles with a diameter of 8 mm were marked on the table. Each target was surrounded by a white area (diameter 60 mm) to increase the saliency of the colored target. Every actor was assigned with two targets of the same color on his or her side of the table. Targets of the same color were 0.35 m apart while the distance of the different colored targets in the center of the table was 0.12 m. The target which was located closer to the body was defined to be the start. Both participants were equipped with a stylus (height 13.5 cm) which had the same diameter as the target and instructed to power-grasp it with their right hand. Additionally they wore SONY stereo headphones (MDR-XD200) with a connection to the control PC. Headphones were used to trigger the beginning and end of a trial via a short acoustical beep. Movements were recorded using an infrared tracking system (PTI Visualeyez II VZ4000). Wired LEDs were attached to the top of each stylus and tracked with a camera bar mounted at the ceiling. The tracking system had an online sampling rate of 30 Hz for calculating the start signal delays (see section Procedure) and an offline sampling rate of 200 Hz for data recording.

During obstacle present trials, a vertical obstacle (height: 0.175 m, width: 0.6 m) was positioned in the workspace of one participant. It was placed orthogonally to movement direction at half the distance between targets, see **Figure 1**.

Note that only one participant of the dyad was *hampered* by an obstacle in 50% of all trials (HAMP). The other participant

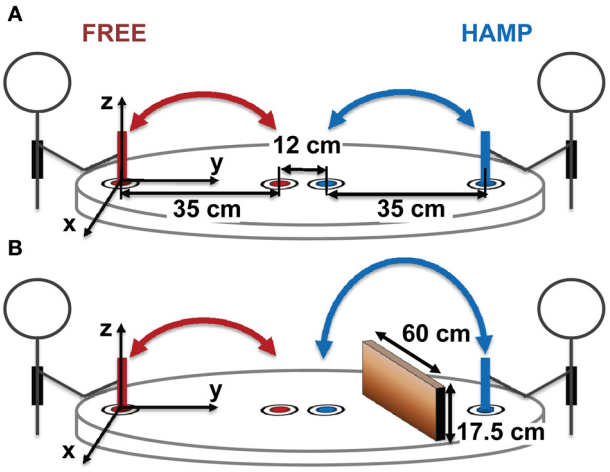

FIGURE 1 | Experimental Setup. (A) configuration without obstacles, **(B)** configuration with obstacle for HAMP. Both participants repetitively moved a stylus with their right hand from one target position (close to them) to another (in the middle of the table) and back.

always acted without an obstacle in his/her *free* movement path (FREE). Note also that both participants were always able to see all four targets, even when the obstacle was present.

PROCEDURE

Before the beginning of each trial, participants rested in the closer target with their stylus oriented orthogonally to the table. They were instructed to begin moving with the acoustical start signal, lift the stylus from the individual start position to the further apart target, tap on the target, move back and tap on the start position again. This procedure was repeated continuously. After both participants performed at least 10 cycles each, the tracking system automatically triggered an acoustical stop signal. Note that participants were not informed about the cycle counter. Also, only start and stop signals were provided. There was no synchronization signal or any other rhythmical guideline. Moving forward, tapping, moving backward and tapping again will be considered as one *cycle*.

Instruction remained the same when an obstacle was present. However, participants were told not to touch or collide with the obstacle. Thus, the obstacle required lifting the stylus over it and with this a change of trajectory was induced.

In order to avoid synchronization to emerge only because of a simultaneous start trigger, different cycle-dependent timings of start signals were calculated online which resulted in three different *start delays*: (1) *zero-cycle*: the start signal was presented simultaneously for both participants, (2) *quarter-cycle*: the start signal for the follower was presented when the beginner had passed half the way to the second target; (3) *half-cycle*: the start signal for the follower was presented when the beginner had reached the second target.

Each dyad performed 12 sets of 6 trials, which results in 72 trials (720 cycles) in total. Within each set, start delay was kept the same while the *configuration* (*congruent*: both participants did not have to clear the obstacle or *incongruent*: one participant had to clear the obstacle) was randomly assigned for each trial and randomized within each set. In sets with start delays quarter- and half-cycle, being beginner was also randomly assigned to one participant and counterbalanced within each set.

Note that participants were naïve as to the purpose of the experiment. Participants were not instructed in any way to synchronize their movements or to adapt their movements to each other. This allowed us to explore if and how synchronous behavior emerges naturally.

DATA PREPARATION

Movement data was recorded in 3-dimensions over time, i.e., for every data point there is information on when it was recorded and the position in x, y and z with origin at the closer target, see **Figure 1**. Here, x refers to horizontal deviation of the movements, y to the progress of forward and backwards movements and z to the elevation above the table surface. Data was prepared, processed and segmented in Matlab; statistical analyses were performed in SPSS.

For every trial, movement onset was calculated as the first time the z-component of the movement crossed 0.005 m. Data analysis only considered movement data after the latest movement onset per trial. Thus, data analysis was always on joint action, not on single action.

For being able to look at the emerging behavior and potential adaptation process, in every trial movement data of each person was segmented into half-cycles (forwards and backwards segments). For segmentation, the times $t_y(n)$ of the trajectory's y-component inflection points were determined, where $n \in N$ counts the amount of tapping actions per trial, see **Figure 2**. As the y-component describes the movement direction between target points, each inflection point represents a turn in direction and thus indentifies a tapping time. From the timestamp of $t_y(n) = t_z(n)$ a temporal window defined by $t_{z2}(n)$ and was $t_{z2}(n)$ determined as

$$t_{z1}(n) = (t_z(n-1) + t_z(n))/2 \quad (1)$$

$$t_{z2}(n) = (t_z(n) + t_z(n+1))/2 \quad (2)$$

Following this, $z_m(n)$ was determined as the trajectories z-component value at time $t_{zm}(n)$ which was calculated as

$$t_{zm}(n) = (t_{z1}(n) + t_{z2}(n))/2 \quad (3)$$

The actual entry and exit to the dwelling phase of the nth tapping was then determined by detecting the closest intersection of the z-component of the trajectory with $t_{zm}(n) + 0.005m$ before and after $t_{zm}(n)$. Data was visually checked and all trials not captured with the automated procedure were manually corrected. Trials in which obstacles were hit and/or an early/late start was detected, were excluded. Overall this resulted in 88% valid trials.

DATA ANALYSIS AND DEPENDENT VARIABLES

Data Analysis was performed in three steps. First, it was determined if the spatial manipulation of the experiment was successful, i.e., if HAMP extended his/her trajectory during obstacle present trials as measured by the *path length* (PL) in 3-dimensional space. During this step it was also checked whether

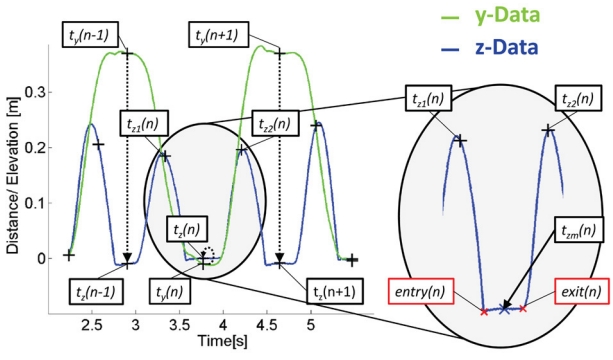

FIGURE 2 | Principle of data segmentation shown on exemplary movement data of the free actor in the congruent configuration. The y-component (green) is used for tapping event detection while dwell time and movement time are determined by the isochronic z-component (blue), see text for more detailed explanation.

the obstacle for HAMP had an impact on the PL of the free actor.

In a second step, the emergence of synchronization was checked over all possible conditions. Therefore, phase data was calculated as described in Mörtl et al. (2012) using the Hilbert-transform (spectral method). From the resulting phase data, the dyadic phase difference (*relative phase*) was calculated for every data point per trial. This resulting relative phase data was clustered into nine pi/9 (20°) relative phase regions (Schmidt and O'Brien, 1997; Richardson et al., 2007; Coey et al., 2011) by counting and accumulating the times the relative phase was in one of the defined regions. Of the accumulated data, percentages were calculated for each condition, see **Figure 4**. For creating a reference, data from non-interacting participants was combined and the resulting phase relation was determined. Therefore each participant's data was combined with all data from all other participants within the respective conditions and clustered as described previously. Here, participants never interacted with each other. Therefore this data should reflect a case in which no synchronization emerges.

Furthermore, for having some information on the quality of the synchronization, the *cross spectral coherence* was calculated as

$$\text{Coherence} = 1 - \text{CV} \tag{4}$$

where CV is the circular variance of the relative phase over time (Kreuz et al., 2007). The coherence can vary between 0 and 1. If phase differences would be distributed uniformly, the coherence would equal 0, while in perfect synchronization, the coherence would equal 1.

In a third step, general adaptation behavior was explored using PL, *movement time* (MT) and *median velocity* (MV) for each half-cycle. All measures were averaged per trial and actor and compared between conditions.

RESULTS

SPATIAL BEHAVIOR

For the path length, a $(2 \times 3) \times 2$ mixed repeated measures ANOVA was performed with the within-subject factors *configuration* (congruent, incongruent) and *start delay* (zero-cycle, quarter-cycle, half-cycle), and the between-subject factor *actor* (HAMP, FREE). Prediction based comparisons by means of dependent *t*-tests (1-tailed) were performed to clarify intrapersonal differences (Field, 2009).

Path length (PL) was determined as the length of the 3D-trajectory performed during the movement interval of each cycle and direction (forwards, backwards). The median was calculated of all half-cycle trajectory lengths per trial and averaged per direction and participant.

Comparison of path lengths revealed that the trajectories were significantly longer for both forwards and backwards movements in the incongruent configuration, see **Figure 3** and **Table 1**. In general the hampered actor extended the trajectory. Although the free actor also slightly extended the path length during the incongruent configuration, this effect was only marginally significant, see **Table 2**.

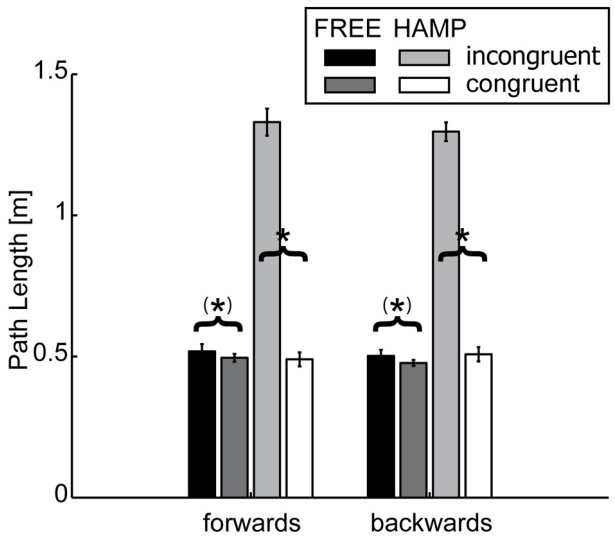

FIGURE 3 | Path Length (PL) of FREE and HAMP in both configurations. Error bars depict the standard error of the mean over participants within one condition. In the obstacle present configuration, the hampered actor extends the trajectory to avoid possible collisions. But also the free actor slightly increases path length if HAMP has to clear the obstacle. *Denotes a significance of $p < 0.05$; (*) stands for marginally significant results ($0.05 < p < 0.1$).

Table 1 | Results of (2 × 3) × 2 mixed design repeated measures ANOVAs with the within subject factors configuration (congruent, incongruent) and start delay (zero-cycle, quarter-cycle, half-cycle) and the between subject factor person (HAMP, FREE).

		Forwards/distant target	Backwards/close target
PL	C	$F_{(1,\ 18)} = 320.69$, $p < 0.001$*	$F_{(1,\ 18)} = 469.38$, $p < 0.001$*
	P	$F_{(1,\ 18)} = 121.31$, $p < 0.001$*	$F_{(1,\ 18)} = 209.33$, $p < 0.001$*
	C × P	$F_{(1,\ 18)} = 287.96$, $p < 0.001$*	$F_{(1,\ 18)} = 412.28$, $p < 0.001$*
DT	C	$F_{(1,\ 18)} = 2.51$, $p = 0.131$	$F_{(1,\ 18)} = 0.45$, $p = 0.510$
	P	$F_{(1,\ 18)} = 0.12$, $p = 0.730$	$F_{(1,\ 18)} = 0.46$, $p = 0.833$
	C × P	$F_{(1,\ 18)} = 9.38$, $p = 0.007$*	$F_{(1,\ 18)} = 5.40$, $p = 0.032$*
MT	C	$F_{(1,\ 18)} = 40.30$, $p < 0.001$*	$F_{(1,\ 18)} = 35.71$, $p < 0.001$*
	P	$F_{(1,\ 18)} = 3.88$, $p = 0.064$	$F_{(1,\ 18)} = 0.99$, $p = 0.334$
	C × P	$F_{(1,\ 18)} = 27.68$, $p = 0.001$*	$F_{(1,\ 18)} = 18.58$, $p = 0.001$*
MV	C	$F_{(1,\ 18)} = 85.97$, $p < 0.001$*	$F_{(1,\ 18)} = 135.01$, $p < 0.001$*
	P	$F_{(1,\ 18)} = 9.23$, $p < 0.007$*	$F_{(1,\ 18)} = 12.36$, $p < 0.002$*
	C × P	$F_{(1,\ 18)} = 85.94$, $p < 0.001$*	$F_{(1,\ 18)} = 135.18$, $p < 0.001$*

P-values are reported to be significant "" if the 2-tailed significance level $p < 0.05$. Statistics for start delay are not provided as they were all not significant, all $p > 0.06$. PL, Path Length; DT, Dwell Time; MT, Movement time; MV, Median Velocity; C, Configuration; P, Person.*

SYNCHRONIZATION

Distribution of relative phase

To check whether synchronization emerged under incongruent conditions, the distribution of relative phase was calculated, see section Data Analysis and Dependant Variables. A $2 \times 3 \times 9$

repeated measures ANOVA was performed for both configurations (congruent, incongruent) with the within subject factors *coupling* (yes, no), *start delay* (zero-cycle, quarter-cycle, half-cycle) and *phase region* (9 regions from 0 to pi).

Table 2 | Results of pairwise directed comparisons to clarify intrapersonal behavioral differences between configurations.

	Actor	Forwards/distant target	Backwards/close target
PL	HAMP	$t_{(9)} = 18.51$, $p < 0.001$*	$t_{(9)} = 22.74$, $p < 0.001$*
	FREE	$t_{(9)} = 1.40$, $p = 0.098$	$t_{(9)} = 1.77$, $p = 0.055$
DT	HAMP	$t_{(9)} = -2.41$, $p = 0.020$*	$t_{(9)} = -1.58$, $p = 0.074$
	FREE	$t_{(9)} = 2.80$, $p = 0.011$*	$t_{(9)} = 2.56$, $p = 0.016$*
MT	HAMP	$t_{(9)} = 5.87$, $p < 0.001$*	$t_{(9)} = 5.35$, $p < 0.001$*
	FREE	$t_{(9)} = 3.58$, $p = 0.003$*	$t_{(9)} = 3.01$, $p = 0.008$*
MV	HAMP	$t_{(9)} = 9.87$, $p < 0.001$*	$t_{(9)} = 12.02$, $p < 0.001$*
	FREE	$t_{(9)} = 0.002$, $p = 0.499$	$t_{(9)} = -0.014$, $p = 0.495$

P-values are reported to be significant "" if the 1-tailed significance level p < 0.05. PL, Path Length; DT, Dwell Time; MT, Movement time; MV, Median Velocity.*

For both configurations we found a significant main effect of phase region, congruent: $F_{(8,\ 72)} = 12.83$, $p < 0.001$, incongruent: $F_{(8,\ 72)} = 4.55$, $p < 0.001$, indicating a non-uniform distribution of relative phase angle occurrence over the nine regions. **Figure 4** shows the distribution of relative phase angles over phase regions resulting from the three start delay conditions. Significant interaction effects were found for coupling x phase, congruent: $F_{(8,\ 72)} = 12.14$, $p < 0.001$, incongruent: $F_{(8,\ 72)} = 3.38$, $p = 0.002$, reflecting the peaks for in-phase and anti-phase synchronization in the coupled case for both configurations. Also the phase region by start delay interaction reached significance in both configurations, congruent: $F_{(16,\ 144)} = 9.02$, $p < 0.001$, incongruent: $F_{(16,\ 144)} = 3.41$, $p < 0.001$. This is explained by the fact, that starting at the same time (zero-cycle) resulted in mainly in-phase coordination (peaks at 0°), while a shift in start delay (quarter-cycle or half-cycle) more often resulted in anti-phase coordination. The three-way interaction was also significant in both configurations, congruent: $F_{(16,\ 144)} = 9.08$, $p < 0.001$, incongruent: $F_{(16,\ 144)} = 3.64$, $p < 0.001$, which underlines that the start delay x phase region interaction was significant and present in both configurations when coupling was provided in comparison to the non-coupled case reflected by the permuted data.

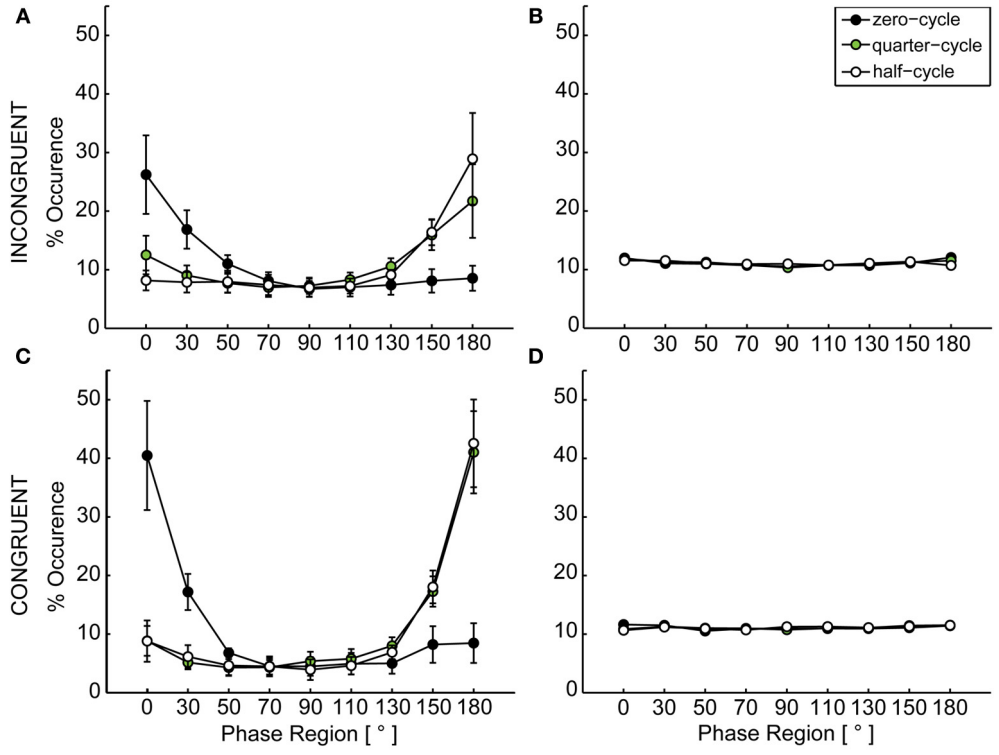

FIGURE 4 | Distribution of relative phase. (A) shows the dyadically coupled data for the incongruent configuration, **(B)** the uncoupled permuted data for the incongruent case, **(C)** the dyadically coupled data for the congruent configuration and **(D)** the uncoupled permuted data for the congruent configuration. In **(A)** and **(B)**, error bars depict the standard error of the mean over participants within one condition. In **(C)** and **(D)**, the average standard error over nine phase regions was 0.61 for the incongruent and 0.52 for the conguent configuration and thus too small to be depicted. In both dyadically coupled configurations the distribution shows clear peaks at 0° (in-phase relation) and 180° (anti-phase relation). Depending on the induced start delay, participants mainly ended up in in-phase relation (after zero-cycle delay) or anti-phase relation (after quarter-cycle and half-cycle delay).

Coherence

For finding the degree to which people were correlated, the cross spectral coherence was calculated for each configuration, see section Data Analysis and Dependent Variables. A 2 × 3 repeated measures ANOVA on the within subject factors configuration (congruent, incongruent) and start delay (zero-cycle, quarter-cycle, half-cycle) did not yield any significant effect, all $p > 0.1$. Nevertheless the coherence was numerically higher when the obstacle was absent in all start delay conditions, see **Figure 5**. In the congruent configuration, coherence was 0.73 ± 0.13 (*SE*) while in the incongruent configuration coherence was only found to be 0.51 ± 0.11 (*SE*).

TEMPORAL BEHAVIOR

In section Spatial Behavior it was reported that the obstacle caused prolonged trajectories for the hampered actor, while the free actor only marginally extended the trajectories during incongruent trials. Nevertheless synchronization emerged in both configurations. Thus, a certain temporal adjustment must have taken place. Else, if no temporal adjustment happened, synchrony would not emerge because the time that is required to perform the prolonged trajectory naturally extends the time to perform the shorter trajectory at the same velocity. With this, a continuous drift in phase relation would be caused and the distribution of relative phase would be equal to the permuted data, see for example **Figure 4B**.

In general, there are several possibilities for establishing synchronization in an incongruent configuration. In this context different aspects can be regarded: (i) in which temporal period the adjustment happens and (ii) who makes the adjustments. Regarding temporal period, there are three possibilities for adaptation. First, people could adapt during their movement period between targets, second they could wait for each other in either one or both target points, or third, they could apply both strategies mentioned before and continuously adapt.

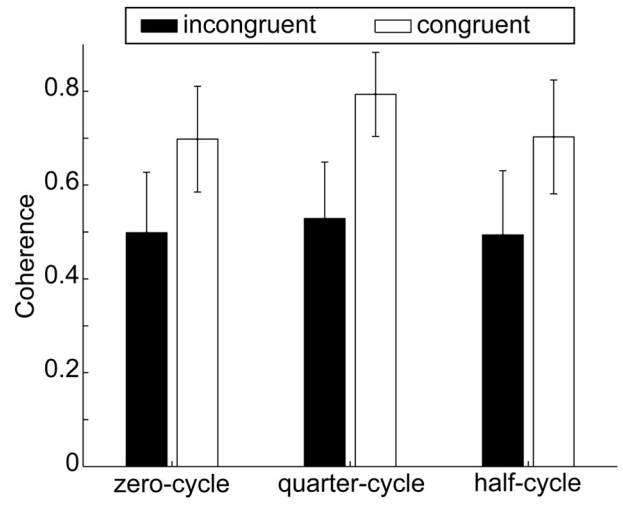

FIGURE 5 | Coherence for both obstacle configurations and in the three start delay conditions. Error bars depict the standard error of the mean over participants within one condition. Numerically coherence is lower in the obstacle present configuration; however the difference between conditions was not significant.

Regarding the aspect of who is adjusting, again three possibilities apply: one or the other actor could take over the whole load and adjust the movement to the other actor. More specifically this means, that if the free actor does not change behavior, the hampered actor would have to take all the effort. Thus, he/she could increase movement velocity and/or reduce dwell times in the targets to keep up with the free actor whose trajectory is only marginally extended. If, as the second possibility, the free actor takes over all the adjustment effort, then one would expect a reduction in his/her movement velocity or an increase in dwell times—as an extension of the trajectory is already shown to be only marginal there. However, if as a third possibility, mutual adaptation and thus a joint effort is required to establish synchronization (see Konvalinka et al., 2010), we should find adaptation in the movement profiles of both actors—even when only one actor has to clear the obstacle.

For all temporal measures (2 × 3) × 2 mixed repeated measures ANOVAs were performed with the within-subject factors *configuration* (congruent, incongruent) and *start delay* (zero-cycle, quarter-cycle, half-cycle), and the between-subject factor *actor* (HAMP, FREE). Prediction based comparisons by means of dependent *t*-tests (1-tailed) were performed to clarify intrapersonal differences (Field, 2009).

Dwell time (DT) and movement time (MT)

Dwell time (DT) was determined as the time participants spent in one of the targets. This time was determined by the entry and exit indices described in section Data Preparation. The remaining time in between was considered as the time in which participants were actually moving their arm forwards or backwards. These time periods are called movement time (MT) in the following.

Regarding DT, the only significant effect was a configuration x actor interaction in both targets, see **Table 1**. During incongruent configuration, the actor who had to clear the obstacle significantly reduced his/her dwell time, while the actor without the obstacle significantly increased the dwell time compared to the congruent case, see **Figure 6**. This means that during the dwelling phase, a joint effort is undertaken.

For MT, a significant main effect of configuration was obtained for both movement directions, see **Table 1**. Also the main effect of actor reached significance in both movement directions. However both main effects can be explained by the highly significant configuration x actor interaction indicating a much higher movement time for HAMP during incongruent configuration. Furthermore, pairwise comparison showed that FREE also significantly increased movement time during forwards and backwards movement if the obstacle was present, see **Table 2**.

Overall, no main or interaction effect was obtained for start delays, all >0.06, indicating that the behavioral differences found here apply for both the emergence of in-phase and anti-phase synchronization.

Median velocity

Velocity was calculated from the distance between data points in Cartesian coordinates. For smoothing the data, a fourth order

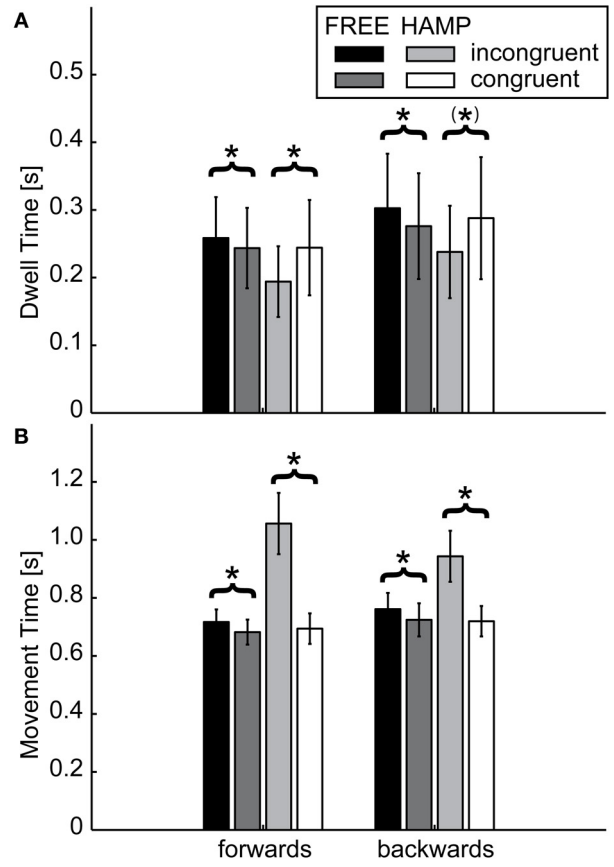

FIGURE 6 | (A) Dwell Times and **(B)** Movement Time of FREE and HAMP in both configurations. Error bars depict the standard error of the mean over participants within one condition. While the hampered actor increases movement time to account for the prolonged trajectory, the free actor also moves slower if the obstacle is present. However regarding the time spent in target positions, the hampered actor dwells less if an obstacle is present, while the free actor increases dwell times. Thus, the free actor "waits" for the interaction partner and acts more predictable. *Denotes a significance of $p < 0.05$; (*) stands for marginally significant results ($0.05 < p < 0.1$).

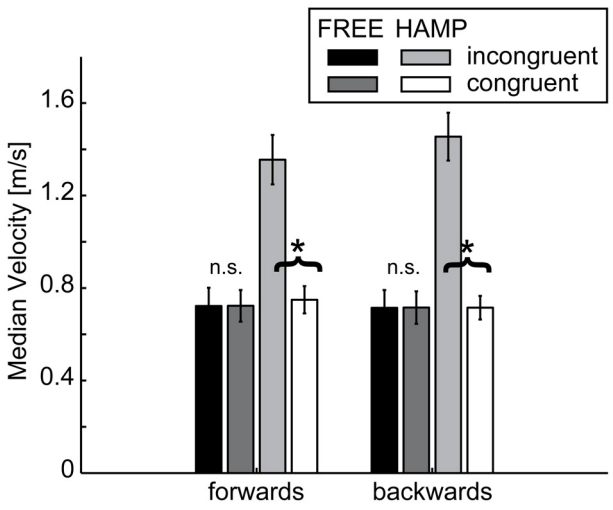

FIGURE 7 | Median Velocity of FREE and HAMP in both configurations. Error bars depict the standard error of the mean over participants within one condition. The hampered actor on average increases movement velocity while passing the obstacle while the free actor's velocity is not affected if an obstacle is present in the overall configuration. *Denotes a significance of $p < 0.05$; n.s. is not significant.

low-pass Butterworth filter with a cut-off frequency of 10 Hz was applied. The resulting phase shift was corrected by applying the same filter reversely. For each forward and backward movement the median velocity (MV) was determined and averaged over each trial and dyad per condition.

A significant main effect was observed for configuration in both directions indicating a higher MV during the incongruent condition, see **Figure 7** and **Table 1**. However, also the factor actor yielded a significant main effect in both movement directions, indicating a higher MV for the actor who had to clear the obstacle, see **Table 1**. Both effects can be explained by the significant configuration x actor interaction: in both forward and backward movements, HAMP moved significantly faster if the obstacle was present, while the MV of FREE was not affected.

No main or interaction effect was found for start delays, all $p > 0.15$. This indicates that MV has no influence on the emergence of either in-phase or anti-phase synchronization.

DISCUSSION

With the present study we investigated the question whether movement synchronization also emerges between target-directed arm movements of two people when their performed trajectories are incongruent. An obstacle was included into one actor's workspace which caused a prolongation of trajectory. Due to the incongruence of movement trajectories of both actors, we expected movement interference to emerge which could cause synchronization to break down. On the other side, also the effort of obstacle avoidance might lead to non-synchronous behavior.

MOVEMENT SYNCHRONIZATION

If movement trajectories are incongruent during dyadic interaction in a target-directed task, movement synchronization still emerges as indicated by peaks in the distribution of relative phase around 0 and 180° compared to the non-synchronous case. Numerically, the cross spectral coherence was smaller in the incongruent configuration in which the obstacle was present. As the difference in coherence is not significant, this finding might mainly reflect the higher effort which comes with the need to enable a useful strategy for compensating with the more difficult situation.

MOVEMENT INTERFERENCE

In the incongruent case, when the hampered actor had to clear the obstacle and therefore extended the trajectory, the trajectory of the free actor was also marginally extended.

Movement interference of motor contagion theories predict that if observing somebody else performing an action incongruent to our own action, our own action performance is biased and variability is increased (Kilner et al., 2003; Stanley et al., 2007). Following this idea, one could argue that the small increase

of path length of the free actor in obstacle-present trials only happened due to the aforementioned effect and has nothing to do with movement adjustment. However, if the prolongation of the trajectory only appeared due to movement interference, the dwelling behavior as an adaptation process would lose its purpose. An alternative explanation comes from the idea of the so-called *rhythmic movement interference* (RMI), which even predicts increased deviations while observing incongruent movements (incongruent trajectories). These deviations however are not thought to be a problem to the emergence of synchronization (as the motor contagion theory would predict) but rather the enabler for it. The RMI states that while observing somebody performing movements incongruent to the own ones, additional degrees of freedom are liberated by deviating from one's original plane. These additional degrees of freedom stabilize coordination in situations in which it would otherwise be unstable (Fink et al., 2000; Milliex et al., 2005; Richardson et al., 2009; Romero et al., 2012). In this context, Fink et al. (2000) showed that when limiting a bimanual pendulum swinging task to a single plane, transitions from anti-phase to in-phase synchronization (the more stable state) appeared. These transitions were absent if the swinging plane was not restricted. Instead, deviations from the instructed plane were observed, which were obviously used to sustain anti-phase coordination. For the present study this implies that the free actor could have adjusted to the higher variability of the hampered actor in the obstacle-present case by showing higher deviations from the instructed direction of motion (forwards/backwards) and vice versa. Thus, the RMI would allow for explaining how movement synchronization was enabled and coherence was only slightly decreased.

Another interesting idea for explaining the adaptation of the free actor to the hampered actor in space and time is the notion of hand path priming by the use of spatio-temporal forms (van der Wel et al., 2007). If an obstacle is present in the shared peri-personal space, the free actor might take on the predefined spatio-temporal forms that are defined for obstacle avoidance and with this prepare for accounting to the hampered actor's behavior. This idea is supported by findings of Castiello (2003). In an experiment in which one person had to reach and grasp an object in the presence of a distractor, the subsequent similar action without a distractor of the person previously observing this action was biased in the same way as the movement of the first person with distractor. Castiello also showed, that both persons paid similar attention to the distractor, as indicated by eye movements, irrespective of whether they were affected by it. Thus, in the present study the obstacle might afford a different spatio-temporal form—also for the free actor and regardless of the need to clear it, only because it is there.

The fact that the spatial adaptation of the free actor was not very striking might be owed to the relative distance between participants. The shared workspace was relatively close to the border of each actor's peri-personal space (Previc, 1998) and thus the movements of the free actor were not as affected as they might have been in closer interaction. Furthermore, participants were sitting opposite to each other, not next to each other. This implies that the deviations induced by the obstacle in the movement trajectory of the hampered actor might have been hard to guess because they had to be estimated frontally, not from the side.

MUTUAL ADAPTATION AND JOINT ACTION

Nevertheless, despite all observed difficulties, synchronization emerged when an obstacle was present through adaptation by one or both interaction partners. The hampered actor had to extend the movement trajectory, and thus movement trajectories of the dyad were incongruent. Here, compensation for the prolonged trajectory, led to an increase of movement velocity. This is especially interesting in the light of known obstacle avoidance strategies which show that if an obstacle has to be cleared, movement velocity is decreased in order to increase accuracy of the movement and avoid potential collisions with the obstacle (Tipper et al., 1997; Coppard et al., 2001; Chapman and Goodale, 2008). However these findings derive from discrete and non-repetitive tasks in which participants were not in an interaction situation at the same time.

Vesper et al. (2009) showed that while jointly building a marble track by moving wooden building bricks from a defined start to a defined target position, movement velocity was increased compared to performing the same task alone. Similar to the present study, a decreased movement time and an increased path length (transport path) was observed during the joint action condition compared to single action. The authors argued that the increase of speed and the increased deviation during joint action in comparison to single action might be explained by the intention of participants to clear the joint workspace as soon as possible in order to clear the space for the interaction partner. Following this, also interaction in close space may be treated as dealing with obstacles (the other actor) and thus the reaction could be a constant obstacle/collision avoidance behavior during joint tasks. However, Vesper et al. only focused on the behavior of one person in a joint task and the dynamics of the interaction were not regarded. In the present study the interaction dynamics were one focus and it was shown, that synchronization patterns emerge between interaction partners even if one interaction partner was dealing with obstacle avoidance. Here, the free actor and his/her movements were in the direct field of view of the hampered actor when reaching over the obstacle. Therefore it can also be argued that because both actors were engaged in a repetitive task with the possibility of observing each other, they could not avoid synchronizing their movements (Issartel et al., 2007; Schmidt et al., 2007). In this case, the obstacle avoidance task would be the secondary task, and the discrete obstacle avoidance behavior (slowing down) was sacrificed and higher effort was applied to fulfill the needs (speed up) of successful synchronization. Support for this notion comes from Doumas et al. (2008), who explored movement synchronization in a bimanual repetitive finger tapping task. In their study, taps had to be synchronized to a metronome and had to be performed at different movement amplitudes. If at the same time interval tapping amplitude was higher, movement velocity was increased in order to keep track with timing constraints from the metronome. Thus, when the amplitude has to be increased, a natural reaction is to speed up in order to remain in synch.

In a similar way, movement synchronization with another actor bears temporal constraints. If an actor wants to keep track

with an interaction partner who can perform his/her movements at lower amplitude, the actor has to speed up to keep track with the timing demands of synchronous movements. Therefore, the obstacle in the present study would simply be treated as a "higher amplitude generator" which has to be compensated to reach the joint unintentional goal, namely movement synchronization.

What adds to this argumentation is the finding that also the free actor—who was in no need to react to the obstacle—unintentionally, took part in the compensation process. Participants on the FREE side slightly increased their path length and with this reached a higher movement time if the hampered actor had to clear an obstacle, by on average keeping movement velocity constant. With this strategy, the free actor was always providing a predictable behavior and potentially enabled a successful adaptation of the interaction partner.

On top of that, the free actor increased dwell times in both targets and with this "waited" for the interaction partner during the incongruent configuration, while the hampered actor decreased dwell times in both targets when an obstacle was present. The adjustment of dwell times observed in both actors might also be related to an adjustment of the perceptual center of the perceived event (p-center hypothesis, Morton et al., 1976; Aschersleben, 2002). The p-center hypothesis assumes that each event that is extended over time has a perceptual center that differs from the onset of the stimulus. It is also stated, that its position in time depends on stimulus duration (among others). This also means that if the stimulus duration is increased, then there is a bigger delay between stimulus onset and its perceptual center. This can also be used for synchronization: if the free actor increases dwell times, the hampered actor has more time to estimate the perceptual center and can adjust his/her movements accordingly. However this would only apply if the event which is used to synchronize with each other is the perceptual center of a time period—in contrast to its onset.

Taken together, it seems as if the hampered actor mainly compensates for the increased movement trajectory, while the free actor tries to make this adjustment process as easy as possible. With this, the unintentional goal to synchronize in an incongruent scenario can be reached. In literature it was also claimed, that people actively and mutually adapt to each other's behavior in order to synchronize their movements (i.e., Konvalinka et al., 2010). Adding to this however, our results show that people do not only mutually represent the task (Frith and Frith, 2010; Obhi and Sebanz, 2011; Wenke et al., 2011), they also assign different roles to each other depending on the needs of the task and in order to compensate for the increased effort induced by the obstacle. While one actor operates as compensator, the other one accommodates these compensatory movements by making himself as predictable as possible. This means, that movement synchronization in an incongruent case is not only a merely emerging behavior, it also bears features of a joint action task, in which complementary actions have to be fulfilled in order to reach accomplishment.

CONCLUSION

If the movement trajectories of people engaged in a repetitive target-directed tapping task are incongruent, movement synchronization still emerges. Moreover, if the trajectory of one actor is disturbed by an obstacle, the regular obstacle avoidance strategies (decreased velocity) do not apply—presumably due to prioritization of movement synchronization with the partner. Therefore, different adaptation roles are assigned between interaction partners: while one actor has to deal with a more difficult task (obstacle avoidance), the interaction partner aims to be as predictable as possible by adapting dwell times and maintaining speed. In summary, if a simple component like an obstacle is added to a target-directed tapping task in a shared workspace, movement synchronization not merely emerges between interaction partners; it also requires complementary actions like any higher level joint action task.

AUTHOR CONTRIBUTIONS

Tamara Lorenz, Björn N. S. Vlaskamp, and Sandra Hirche defined the research question on synchronization in goal-directed tasks. Tamara Lorenz, Björn N. S. Vlaskamp, and Anna-Maria Kasparbauer designed the experiment. Anna-Maria Kasparbauer, Tamara Lorenz, and Alexander Mörtl performed the experiment. Tamara Lorenz, Anna-Maria Kasparbauer, Björn N. S. Vlaskamp, and Alexander Mörtl analyzed the data. Tamara Lorenz, Anna-Maria Kasparbauer, Björn N. S. Vlaskamp, Alexander Mörtl, and Sandra Hirche wrote the paper. Björn N. S. Vlaskamp and Sandra Hirche supervised the project.

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7

IMPLEMENTING DYNAMICAL SYSTEMS THEORY FOR HUMAN-ROBOT INTERACTION

Everything must be made as simple as possible.
But not simpler.

— Albert Einstein

7.1 SUMMARY & CONTEXT

Based on the human movement synchronization data recorded in Chapter 4, this paper outlines a step-wise approach to a model for human-human movement coordination in goal-directed tasks. The main purpose of this model is to provide a formal description of human movement synchronization for application in human-robot interaction.

Inspired by the Haken-Kelso-Bunz (HKB) model (Haken et al., 1985), the general idea is to describe the dyadic synchronization behavior by the attractor dynamics of two coupled Kuramoto-oscillators (Kuramoto, 1984). However, based on observations in undirected synchronization tasks, the HKB model proclaims only one generally stable attractor state, namely in-phase relation, while anti-phase is only treated as meta-stable (depending on frequency). In contrast, results from Chapter 4 and Chapter 6 show that in naturally emerging goal-directed movement synchronization, humans establish in-phase as well as anti-phase relations. Therefore, the existing model is extended to account for both attractor states (Fuchs and Kelso, 1994).

If the model should capture the human behavior, it is furthermore necessary to obtain the phase-data of human behavior. Thus, besides the modeling approach, two known methods for transforming motion data into phase are investigated and their influence on the model fit to the experimental data is evaluated. However these methods calculate the phase as a time-continuous signal, while it was shown in Chapter 6 that adaptation happens in different segments or *action primitives* of the movement (dwell time/movement time). Thus, in addition to the established methods, a hybrid approach is introduced. Here, the phase for the dwelling segments in which no movement happens is calculated purely depending on time while the movement segments are represented by a minimum-jerk model of which the instantaneous phase can be obtained by its inversion.

The model parameters coupling strength and frequency detuning are estimated by implementing the differential equation of the phase difference by means of gray box modeling into the PEM-algorithm

(prediction-error minimization) of MATLAB's System Identification Toolbox. The stability properties of the identified model match the relations observed in the experimental data. In short, the model predicts the dynamics of inter-human movement coordination. It can directly be implemented to enable emergent human-robot coordination.

Furthermore, a first (unpublished) exploration of this model in an human-robot interaction setting is reported in Section 7.3. It shows that albeit the model is applicable in human-robot interaction, it reveals a major problem, namely to determine the fine-adjustment or amount of adaptation in mutual coupling between humans and robots.

7.2 REFERENCE & CONTRIBUTION

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Tamara Lorenz and Anna Schubö designed the study; Tamara Lorenz and Alexander Mörtl conducted the experiment; Alexander Mörtl, Tamara Lorenz and Björn Vlaskamp analyzed the data; Alexander Mörtl and Azwirman Gusrialdi developed the modeling approach with contributions from Tamara Lorenz and Sandra Hirche; Alexander Mörtl, Tamara Lorenz, Björn Vlaskamp and Sandra Hirche wrote the paper; Sandra Hirche and Anna Schubö supervised the project.

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ORIGINAL PAPER

Biological Cybernetics

Modeling inter-human movement coordination: synchronization governs joint task dynamics

Alexander Mörtl · Tamara Lorenz · Björn N. S. Vlaskamp · Azwirman Gusrialdi · Anna Schubö · Sandra Hirche

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Abstract Human interaction partners tend to synchronize their movements during repetitive actions such as walking. Research of inter-human coordination in purely rhythmic action tasks reveals that the observed patterns of interaction are dominated by synchronization effects. Initiated by our finding that human dyads synchronize their arm movements even in a goal-directed action task, we present a step-wise approach to a model of inter-human movement coordination. In an experiment, the hand trajectories of ten human dyads are recorded. Governed by a dynamical process of phase synchronization, the participants establish in-phase as well as anti-phase relations. The emerging relations are successfully reproduced by the attractor dynamics of coupled phase oscillators inspired by the Kuramoto model. Three different methods on transforming the motion trajectories into instantaneous phases are investigated and their influence on the model fit to the experimental data is evaluated. System identification technique allows us to estimate the model parameters, which are the coupling strength and the frequency detuning among the dyad. The stability properties of the identified model match the relations observed in the experimental data. In short, our model predicts the dynamics of inter-human movement coordination. It can directly be implemented to enrich human–robot interaction.

Keywords Coupled oscillators · Dynamical model · Human movement coordination · Phase estimation · Phase synchronization

T.L. and A.S. designed the study; T.L. and A.M. conducted the experiment; A.M., T.L. and B.N.S.V. analyzed the data; A.M. and A.G. developed the modeling approach with contributions from T.L. and S.H.; A.M., T.L., B.N.S.V. and S.H. wrote the paper; S.H. and A.S. supervised the project.

A. Mörtl ( ) · A. Gusrialdi · S. Hirche
Institute of Automatic Control Engineering, Technische Universität München, Munich, Germany
e-mail: moertl@tum.de

T. Lorenz · B. N. S. Vlaskamp
Experimental Psychology, Ludwig-Maximilians-Universität, Munich, Germany

A. Schubö
Experimental and Biological Psychology, Philipps-University Marburg, Marburg, Germany

1 Introduction

People coordinate their movements in many situations of daily life. This movement coordination can be *intrapersonal*, e.g., coordination of one's left with one's right arm or *interpersonal*, i.e., coordination with another person. There is a wide range of actions that people can do together and for all these actions movements need to be coordinated. Examples range from handing over objects, manipulating a common workpiece to setting up a table. In order to prevent collisions and injuries in the worst case, the agents are required to keep certain spatial and temporal relations of their actions. People often seem to achieve such coordination without much effort in a smooth manner.

1.1 Synchronization—a ubiquitous feature of human movement coordination

Coordination often comes about as movement synchronization during repetitive action. Synchronization can be understood as the establishment of a bounded temporal relation-

ship between the interacting entities, which is brought about and sustained by a convergent dynamical process. Many examples in literature provide evidence for movement synchronization. When walking in a group, people tend to synchronize their gait (van Ulzen et al. 2008). In experiments requiring relatively simple movements, synchronization is found to be a stable pattern in human behavior. Richardson et al. (2007) introduce a paradigm in which two people are moving next to each other in rocking chairs. They unintentionally rock in synchrony, although different weights attached to the chairs manipulate the frequencies at which they would naturally oscillate without human effort. Similar behavior is observed in tasks in which people have to swing handheld pendulums (Richardson et al. 2005) or are merely moving their legs (Schmidt et al. 1990). Besides these behavioral effects, synchronization affects social relationships. It is found that falling into synchrony with somebody else serves a purpose: it enhances perceptual sensitivity toward each other, fosters cooperative abilities (Valdesolo et al. 2010) and leads to the attribution of more positive characteristics to the interaction partner (Miles et al. 2009). All in all synchronization of movements seems to play an important role in human interactive behavior.

The contribution of this article is a systematic approach to describe human–human interaction (*HHI*) in a quantitative way. Our goal is to provide a description that can be applied directly in human–robot interaction (*HRI*) for its evaluation. We therefore address three research questions in this article: First, is movement synchronization in HHI a phenomenon that also holds in goal-directed tasks? Second, if yes, when does synchronization between humans emerge during such a task and which strategy is applied to do so? Third, how can we capture the observed effects in a mathematical model which is transferable to a robotic agent? The analysis of the experimental data gathered in our previous study (Lorenz et al. 2011) shows that people also synchronize their arm movements in a goal-directed task which is characterized by the need for precise movements. These findings are in line with previous studies on the topic (Schmidt et al. 1990; Richardson et al. 2005, 2007). In general, movement synchronization is found to be a guiding dynamical process which leads to stable coordination patterns in natural HHI. With our approach, we characterize the emerging patterns and the quality of coordination by the extent of phase synchronization. Through system identification based on the experimental data, we obtain a parameterized model which is ready for implementation and evaluation in HRI.

Since modeling of HHI is the central contribution of this article, an overview on related work toward the exploration and modeling of human movement coordination is provided in the following.

1.2 Modeling rhythmic movement coordination

Movement synchronization—as a basic principle of human interactive behavior—is investigated by means of dynamical systems that model interconnected perception–action loops and generate dynamical patterns (Schöner and Kelso 1988; Beek et al. 1995b). Warren (2006) provides a detailed introduction on behavioral dynamics in this context. Pioneering work on modeling intrapersonal coordination of limbs is conducted by Haken et al. (1985). The authors propose a minimal dynamical model of coupled nonlinear oscillators—known as the *Haken–Kelso–Bunz* (*HKB*) *model*—which successfully reproduces the transition between stable coordination patterns during bimanual finger-tapping when changing the cycle frequency as the control parameter. The observed change of attractor basins depending on the extrinsic control parameter is qualitatively described by a sinusoidal potential function.

Several modifications of the HKB model are proposed. Beek et al. (2002) introduce two additional oscillators to represent the level of movement generation through the end effectors while explicitly accounting for the mechanical properties of a human limb. This neuro-mechanical model should foster the fundamental analysis of the interplay between the neural and the effector level during purely rhythmic simple movements. In order to gain deeper insights into the dynamics of human coordination, experimental paradigms which utilize a human's periodical input to drive oscillatory mechanical systems with different eigenfrequencies are applied repeatedly. Schmidt et al. (1993) employ the task paradigm of swinging pendulums originally introduced by Turvey et al. (1986). An extension of the HKB coupling function by a frequency detuning term similar to the coupling function proposed by Cohen et al. (1982) is found to account for both the effects of different eigenfrequencies and external forcing frequencies.

Originally developed to model intrapersonal coordination of movements, dynamical models of coupled oscillators are found to qualitatively explain interpersonal coordination as well. While participants had to swing hand-held pendulums, Schmidt and O'Brien (1997) show the emergence of unintended coordination in a laboratory task. It is argued that the same mechanisms of dynamical self-organization as observed in intrapersonal coordination apply. In a subsequent study, Schmidt et al. (1998) compare the characteristics of intended intra- and interpersonal coordination by applying the same pendulum paradigm. Frequency detuning imposed through different eigenfrequencies and frequency levels are introduced as control parameters. Depending on the frequency level and the intended phase relation, the authors obtain the coupling strength of a local

dynamical model similar to Cohen et al. (1982). The number of coordination breakdowns, the phase fluctuation and the coupling strength reveal interpersonal coordination to be weaker than intrapersonal coordination. However, the regression method to identify the coupling strength relies on a-priori knowledge of the pendulum-wrist system's frequency detuning, which limits the approach to oscillatory effector systems.

Fundamental research work on fitting nonlinear dynamic models to trajectories of human rhythmic movements is conducted by Kay et al. (1987). Observed functional relationships between the external driving frequency and the amplitudes and peak velocities of the movements are found to be reproduced well by a mixture of van der Pol and Rayleigh oscillators with stable parameter fits. The model is fitted to the limit cycle data in the position-velocity phase plane. In a more general approach, Eisenhammer et al. (1991) propose a reconstruction method of time series data based on polynomial dynamical models which are fitted to the vector field of an appropriate state-space representation of the data. While also transients of a pair of coupled oscillators can be reconstructed from simulated data, the method is rather sensitive to noise and requires extensive observation of transient regimes to yield stable results, since the whole state-space region is reconstructed. Inspired by the numerous variations of coupled oscillators models of rhythmic limb movements, Beek et al. (1995a) systematically analyze how different components such as linear and nonlinear elastic and friction terms contribute to the composition of rhythmic movement. Jirsa and Kelso (2005) show in their work on dynamical movement models how the attractor landscape in its state space can be formed to reproduce a variety of both discrete and rhythmic movement behaviors, using their so-called excitators. Elementary human movement trajectories in response to different stimuli are replicated qualitatively by stimulating the respective excitator model. The authors show that their approach extends to coupled dynamical systems as well, yet given a certain action task it may require a more sophisticated design to obtain the desired features of coordinated movement behavior. The aforementioned approaches accurately model basic human motor behavior in rhythmic tasks, yet the movement reproduction and coordination is tightly encoded by the functional state-space representation of the oscillator dynamics, making them less flexible in their application to constrained, goal-directed tasks.

Similar to Beek et al. (2002), de Rugy et al. (2006) propose a neuro-mechanical unit per agent which employs a cross-coupled pair of self-sustained oscillators. The intended modes of coordination while swinging pendulums are replicated as well as the effect of resonance tuning when the pendulums were manipulated individually. Rocking side-by-side in chairs is introduced in a task paradigm involving whole-body movements by Richardson et al. (2007). Analytical results on observed coordination patterns are also related qualitatively to the features of the HKB model, yet explicit modeling is not conducted.

Common to the fundamental research work on rhythmic movement coordination between humans, the exploration and modeling is mostly approached by means of combined oscillatory task-effector systems, such as hand-held pendulums. However, little is known about the coordination behavior of humans in more realistic action tasks, to what extent the fundamental findings and modeling approaches on movement coordination apply, and how the observed effects can be described in a quantitative way.

The remainder of this article is organized as follows: in Sect. 2, we review the design of our experimental task and outline the pursued modeling approach. The reader is provided with the methods used for data reduction and analysis in Sect. 3. Analytical findings, development of the model structure, and the parameter identification are presented in Sect. 4. After discussing the results on dyadic movement coordination in Sect. 5, we draw our conclusions in Sect. 6.

2 Approach

In this section, a brief description of the experimental task is given. Movement data of the experiment also described in Lorenz et al. (2011) are the basis for the investigation of our research questions. We further provide a sketch of our modeling approach including the mathematical definition of synchronization we refer to in this article.

2.1 Experimental task

The investigation of our questions on human movement synchronization places certain requirements on the design of an experimental task. We consider the following points to be relevant for synchronization:

- The task paradigm should integrate *goal-directed* as well as *repetitive* actions which similarly appear in real-life settings. To keep things simple, the task is to execute a repetitive sequence consisting of a forward and a backward movement in a closed trajectory, which we call a *cycle* in the following. Multiple cycles are to be completed in a continuous manner, which allows synchronization to emerge among the agents. The forward as well as the backward movement (half-cycles) are point-to-point arm movements while carrying a tool in hand. This is where goal-directedness comes into play: the tool (a pen) has to be placed on two marked positions on a table alternately. Note that the agents perform identical tasks.
- The *topology of workspaces* is arranged without overlap of the movement trajectories. This enables the agents to

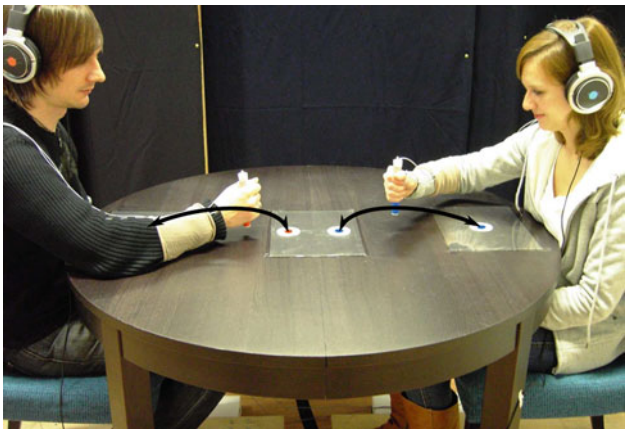

Fig. 1 Experimental setup with two human agents. Participants are sitting face to face. The task is to alternately tap with a pen on two assigned points marked at the table. The action start off is triggered acoustically via headphones. Motion trajectories of the pens are captured by a visual tracking system.

perform in parallel without any interference or demand for collision avoidance, which could restrict movement synchronization.

– During task execution the agents' movements might be affected by *sensory information* that is available of the other agent's movements. In order to provide full visual information, the agents are facing each other without any occlusions. Since they are always able to observe their opponents' movements as well as start and target positions, synchronization is made as easy as possible.

The setup of the laboratory task involving the actions of two agents is depicted in Fig. 1.

To investigate how movement synchronization is initialized, the action start off among the dyad is modulated by triggering it acoustically. Among all possible start off relations, three conditions are supposed to be capable of being differentiated in our experimental task. They are picked as follows: (1) both agents are triggered at the same time (*zero-cycle*); (2) the second agent is triggered when the first agent has passed a quarter of the first cycle, i.e., half the distance between start and target (*quarter-cycle*); (3) the second agent is triggered when the first agent has passed half of the first cycle, i.e., reached the target (*half-cycle*). After the performance of ten cycles, a trial is completed and the agents are triggered to return to their start positions. For details on the experiment, the reader is referred to the appendix.

2.2 Synchronization of coupled dynamical systems

Our goal is to capture the temporal relationship between the dyads' end effector motions in our experiment. To that extent, we propose a modeling approach based on the synchronization of coupled dynamical systems.

2.2.1 Defining synchronization among coupled oscillators

In this article, we adopt the *dynamical systems approach* to describe movement synchronization: the emerging coordination patterns are represented by the attractors of a dynamical system. Thereby attractors denote the regions in the dynamical system's state-space to which the system's trajectories are attracted. In particular, we treat the observed phenomena of movement coordination in an action task as a synchronization problem of two coupled oscillators forming a coupled dynamical system, which is in line with existing modeling approaches (Haken et al. 1985; Rand et al. 1988; Schmidt et al. 1993). The general dynamical equations of two limit cycle oscillators that are mutually coupled are given by

$$\dot{\xi}_1 = F_1(\xi_1) + G_1(\xi_1, \xi_2) \tag{1}$$

$$\dot{\xi}_2 = F_2(\xi_2) + G_2(\xi_2, \xi_1), \tag{2}$$

where ξ_i is a vector of variables of any dimension for oscillator i, F_i represents the limit cycle and G_i is the coupling function that bidirectionally links the oscillators. If the oscillators are harmonic, we can simply write $F_i = \omega_i$ and $\xi_i = \theta_i$, with the oscillator's natural frequency ω_i and its phase θ_i. Depending on the coupling function G_i, the oscillators may interact such that

$$|\Phi_{n,m}(t)| < \epsilon, \text{ with } \Phi_{n,m}(t) = n\theta_1(t) - m\theta_2(t) \tag{3}$$

holds, with the generalized phase difference $\Phi_{n,m}(t)$ and a positive constant $\epsilon \in \mathbb{R}$. Positive constants $n, m \in \mathbb{N}$ allow to detect synchronization of orders $n : m$. Thus, if $\Phi_{n,m}(t)$ becomes constant or fluctuates within some bounds, F_i are synchronized, which is also called *phase locking* (Pikovsky et al. 2001).

Note Since $\Phi_{n,m}(t)$ quantifies the interaction in a single variable, it is also called *collective* in dynamical systems theory. The dynamics of phase synchronization are then described by the trajectory $\Phi_{n,m}(t)$ and its attractors determine the collective behavior of the coupled dynamical system.

2.2.2 From coupled oscillators to movement coordination

Following the definition of phase synchronization, the concept of our systematic approach to model HHI is outlined in Fig. 2. Each of the action tasks 1 and 2 is represented by the agent's end effector positions over time, which we call the motion trajectory in the following. Since the interaction of the coupled oscillators is described by the evolution of its phases, the transformation between motion trajectories and phases is required. It provides the phase of an action task, which models one agent's observation of the other's action. If the transformation is bijective, it can also provide the motion trajectory of a robotic agent and model the generation of

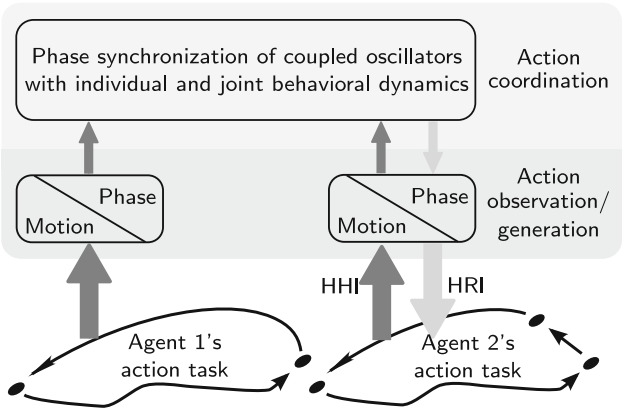

Fig. 2 Overview scheme depicting the two-layered model of movement coordination. Agents 1 and 2 jointly engage in repetitive actions. The observed actions are transformed to phases in the lower layer. In the upper layer, the action coordination is governed by the individual and joint behavioral dynamics modeled as coupled phase oscillators. *Dark arrows* represent the modeling stage conducted in this article (HHI). *Light arrows* outline the envisaged stage of action generation when the scheme is deployed to a robotic agent 2 (HRI).

actions in HRI. In Lorenz et al. (2011) our experimental setup for investigation of human–robot movement coordination is outlined. Within this study, we restrict the investigation of these transformations to model action observation in HHI.

Note As indicated in Fig. 2, the agents' action tasks do not necessarily need to be identical, as long as the motion trajectories can be transformed to phase representations.

Each agent's individual behavior regarding the task progress is represented by a self-sustained phase oscillator with a constant natural frequency. Interaction is modeled through the coupling function, hence temporal coordination patterns as a result of the agents' joint behavior are resembled by phase synchronized oscillators. Both the above transformations as the required analytical tool and the dynamical system model designed to capture the agents' interactive behavior are presented in the following.

3 Analytical methods

In this section, we provide a set of analytical tools to capture and characterize movement synchronization between the agents, a prerequisite to the model design. Note that for reasons of clarity, the presented methods are derived for a single agent unless otherwise stated. If necessary, subscripts 1, 2 are used to indicate correspondence to agents 1 and 2, respectively. For illustration purposes, parts of the presented methods are exemplified based on the experimental data.

3.1 Data reduction to the effective task space

The experimental data gathered within this study consist of the agents' end effector positions over time, i.e., the motion trajectories expressed in a three-dimensional Cartesian frame C (see Fig. 3). Data complexity can be reduced to simplify the analysis, if only the information of the data required for a minimal description of the task is kept. The three-dimensional motion trajectory of each agent is projected into a one-dimensional subspace spanned by the vector difference of the respective target and starting point, as illustrated in Fig. 3. This projection preserves the temporal relation of the agents' end effectors regarding the action task, and thus represents the *effective task space*. Further analysis is conducted based on the one-dimensional motion trajectory $x(t)$. The movement onset is defined as the instant of time when the difference between the position of the end effector x and its initial starting position exceeds 5 mm for the first time.

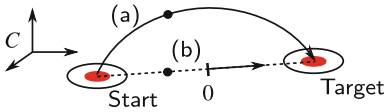

Fig. 3 **a** Sample three-dimensional motion trajectory and **b** projected one-dimensional trajectory $x(t)$ between the agent's start and target point. The origin 0 of the task space is set such that $x(t)$ is zero-mean.

3.2 Transforming the motion trajectory to phase

In order to investigate dyadic phase synchronization, we present three methods transforming the motion trajectory $x(t)$ into a phase $\theta(t)$. Since we are not only interested in steady-state synchronization but also in the potentially transient process leading to phase synchronization, appropriate techniques have to be able to reflect *non-stationary* features of the data into an *instantaneous* phase.

3.2.1 State-space method

Assuming harmonic or quasi-harmonic movements, a two-dimensional state-space $(x, \dot{x})$ can be defined. It is sufficient to describe the state of a one-dimensional oscillatory system. When the motion trajectory is plotted in its state space, the cyclic nature of the movements becomes obvious, see Fig. 4. The phase of the oscillatory system

$$\theta(t) = \arctan\left(\frac{{}^n\dot{x}(t)}{-{}^n x(t)}\right), \tag{4}$$

can be extracted from the state-space trajectory, with

$${}^n\dot{x}(t) = \frac{\dot{x}(t)}{|\hat{\dot{x}}|} \text{ and } {}^n x(t) = \frac{x(t)}{|\hat{x}|}$$

being the normalized velocity and position. The constants $\hat{\dot{x}}$ and $\hat{x}$ denote the extrema of the velocity and position, respectively, observed in the motion trajectory, which can be updated on-line after each half-cycle. In this context,

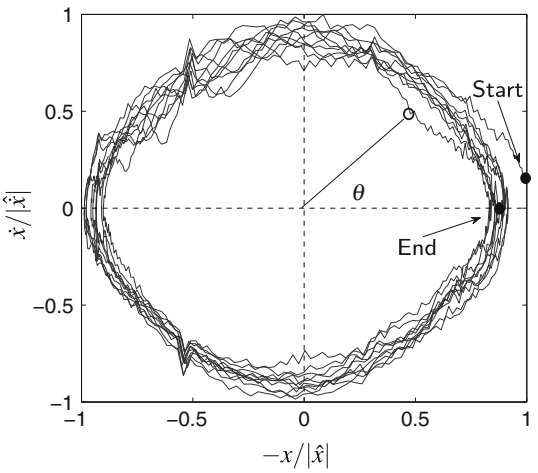

Fig. 4 Normalized state-space trajectory for an experimental trial with ten cycles, where the normalized velocity is plotted against the normalized position. Trajectories form a closed curve with an approximately circular shape between movement start and end. The position x is inverted to obtain a phase θ increasing over time.

Varlet and Richardson (2011) provide a benchmark on continuous phase computation using non-stationary, oscillatory test signals and emphasize the superior performance when half-cycle normalization is applied. The state normalization provides a phase characteristic widely independent of the actual physical constraints of human movements, i.e., the peak amplitudes and velocities.

Note The state-space method is especially well-suited for real-time analysis as long as the motion trajectory is quasi-harmonic. For more complex tasks, the state-space trajectories will differ from simple circular shapes. In such case, the only way to obtain a meaningful phase with this method is band-pass filtering, which selects only a single frequency component or feature of the motion trajectory, respectively, to be represented in the phase. If the measurements are noisy, low-pass filtering of $\dot{x}$ may be required, which introduces an additional phase lag in real-time estimation.

3.2.2 Spectral method

Comparisons of the spectral signal analysis methods (short-time) *Fourier-*, *Hilbert-* and *wavelet-transform* show equivalent results due to their formal equivalence when their filter kernels are parameterized accordingly (Bruns 2004). In this article, we adopt the *analytic signal concept* based on the Hilbert transform for computing a phase (Rosenblum and Kurths 2007). The Hilbert transform provides the instantaneous phase and amplitude of the signal[1] $x(t)$ via construction of an analytic signal $\zeta(t)$, which is a complex function of time defined as

$$\zeta(t) = x(t) + j\tilde{x}(t) = A(t)\mathrm{e}^{j\theta(t)}, \tag{5}$$

where $\tilde{x}(t)$ is the Hilbert transform of $x(t)$. It is given by

$$\tilde{x}(t) = \frac{1}{\pi}\mathrm{P.V.}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}\mathrm{d}\tau, \tag{6}$$

where P.V. means that the integral is taken in the sense of the Cauchy principle value. The instantaneous amplitude $A(t)$ and phase $\theta(t)$ of the signal $x(t)$ are uniquely defined by (5). Since we focus on the analysis of phase synchronization, we are interested in the phase only given by

$$\theta(t) = \arg\left(\zeta(t)\right). \tag{7}$$

Fourier spectra of the motion trajectories x captured in our experiment show a single sharp peak denoting the mean cycle frequency. Thus, the motion trajectories can be treated as narrow band signals and a meaningful phase can be obtained via the spectral method.

Note The spectral method is nonlocal in time due to the infinite integral bounds in (6). Therefore, its applicability to real-time phase estimation is limited, although it is a well-suited tool for off-line analysis. Both the state-space and the spectral methods presented above require zero-mean motion trajectories to obtain phases that cover an angular range of π per half-cycle, i.e., the movement from the starting to the target point or vice versa, respectively.

3.2.3 Hybrid method

Both the state-space and spectral methods perform well only for quasi-harmonic motion trajectories. In our experimental task paradigm, this requirement is fulfilled. However, repetitive action tasks generally comprise a sequence of heterogeneous *action primitives* which compose the overall motion trajectory, such as elementary point-to-point movements, or even static dwelling periods where the position remains rather constant. Inspired by the fundamental signal-theoretic idea to capture an oscillation's cyclic progress in a continuous instantaneous phase, a novel approach is proposed here that extends the notion of phase to describe the instantaneous progress of an *arbitrary* cyclic action. The goal is to construct an instantaneous, linear phase $\theta(t)$ in $[0, 2\pi]$ from the motion trajectory $x(t)$ previously observed for a single cycle in time $t = [0, T]$ with cycle period T. First, the trajectory has to be segmented into a sequence of P action primitives such that for each primitive $p = 1 \ldots P$ an invertible representation.

$$x_p(t) = f_p(\chi_p) \tag{8}$$

can be found, where $x_p(t)$ approximates the motion trajectory and χ_p represents the relative time in p. In a second step, a piecewise continuous phase

[1] The motion trajectory $x(t)$ is treated as a signal.

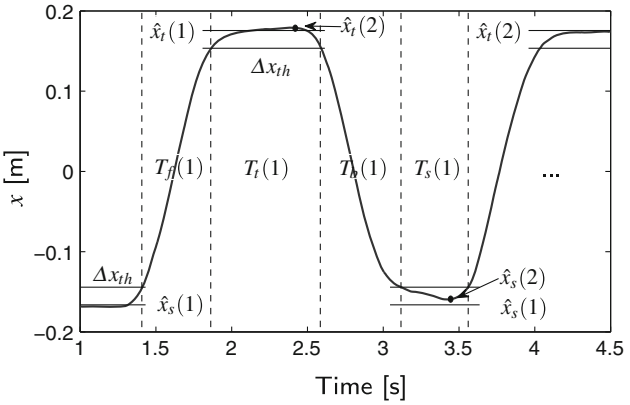

Fig. 5 The first cycle of a representative trajectory with the durations and parameters used for segmentation. *Vertical dashed lines* indicate the threshold-based segmentation into four primitives per cycle. The dwelling periods are considered as separate action primitives.

$$\theta_p(t) = K_p \; f_p^{-1}(x_p(t)) \tag{9}$$

can be obtained, where f_p^{-1} is the inverse of f_p and K_p is a factor scaling χ_p to angular values. Guided by switching conditions between the primitives which can be derived from the segmentation, the phase $\theta_p(t)$ of the current primitive is determined by (9) and accumulated over p in order to obtain a continuous phase $\theta(t)$ of the whole motion trajectory.

In the following, we exemplify the idea of the hybrid method. In Fig. 5, a close-up of a representative trajectory showing the first cycle is given. To assure that invertible representations (8) exist, the motion trajectory can be segmented into four primitives per cycle and parameterized as follows: the forward movement ($p = 1$) in time $T_\mathrm{f}(k)$, the dwell at the target point ($p = 2$) for $T_\mathrm{t}(k)$, the backward movement ($p = 3$) in $T_\mathrm{b}(k)$, and the dwell at the starting point ($p = 4$) for $T_\mathrm{s}(k)$, where k denotes the cycle index. This kind of trajectory segmentation can be performed on-line based on a threshold Δx_{th} with respect to the start and target extrema $\hat{x}_\mathrm{s}(k)$ and $\hat{x}_\mathrm{t}(k)$, as visualized by horizontal lines in Fig. 5.

A possible representation (8) for primitive 1 is the minimum jerk model validated for point-to-point hand movements by Flash and Hogan (1985). It approximates the motion trajectory

$$x_1(t) = \left(\hat{x}_\mathrm{t}(k) - \hat{x}_\mathrm{s}(k)\right) g(\chi_1) + \hat{x}_\mathrm{s}(k), \tag{10}$$

with the fifth-order polynomial

$$g(\chi_1) = 6\chi_1^5 - 15\chi_1^4 + 10\chi_1^3 \tag{11}$$

minimizing jerk, and $\chi_1 \in [0, 1]$ being the relative movement time. In a next step, the minimum jerk model needs to be inverted, which can be done by finding the real root χ_1 of the polynomial (11) in each time step. The phase for primitive 1 can then be written as

$$\theta_1(t) = K_1 \frac{\chi_1 - \chi_\mathrm{th}}{1 - 2\chi_\mathrm{th}}, \tag{12}$$

with the scaling factor

$$K_1 = \frac{2\pi\, T_\mathrm{f}(1)}{T(1)} \tag{13}$$

depending on the movement time $T_\mathrm{f}(1)$ and the cycle period $T(1)$. Note that the threshold-based segmentation cuts off the beginning and the end of motion, thus in (12) the relative time χ_1 is re-normalized by a transformation with χ_th. The value χ_th is the real root of (11) at the value Δx_th.

Since the primitive 2 is characterized by dwelling without considerable motion, a phase representation purely depending on time is proposed

$$\theta_2(t) = K_2 \chi_2 + \theta_1, \tag{14}$$

with the scaling factor

$$K_2 = \frac{2\pi - \theta_1}{T(1) - T_\mathrm{f}(1)}. \tag{15}$$

Note that here, χ_2 is the relative time with respect to the primitive entry. The offset θ_1 in (14) accounts for the phase accumulated previously in primitive 1 and enables a continuous switching of the primitives. Due to symmetry of the primitive sequence, the phases $\theta_3(t)$ and $\theta_4(t)$ are calculated analogously to $\theta_1(t)$ and $\theta_2(t)$. If the primitive durations vary between cycles, the phase does not exactly evaluate $2\pi k$ after the completion of cycle k.

Note Arbitrary complex action sequences can be described on-line with the hybrid method if a feasible segmentation and hybrid representation of the action primitives is found. The estimated phase is an indicator of a repetitive task's relative temporal progress, which is affected however by the chosen parameterization. The approach can be enhanced by learning and prediction techniques to improve the estimation performance.

3.3 Measuring synchronization

In the following, the analytical tools and requirements to detect and measure synchronization based on the agents' phases $\theta_1(t)$ and $\theta_2(t)$ are presented.

3.3.1 Relating the phases—dyadic phase difference

Synchronization between the agents can be detected when their phases are related to each other through the generalized phase difference $\Phi_{n,m}(t)$ given by the definition of synchronization (3). In general, boundedness of the phase difference can be found also for different cycle frequencies of the coupled oscillatory system. For example, one agent performing one cycle while the other completing two cycles can be still

referred to synchronization, which would be called synchronization of order 1:2. The participants in our experiment were performing at similar cycle frequencies, which is indicated by the standard deviation SD $= 0.12$ Hz at a mean $M = 0.73$ Hz over all trials. Thus, the analysis of synchronization can be restricted to the order 1:1 by calculating the dyadic phase difference

$$\Phi(t) = \Phi_{1,1}(t) = \theta_1(t) - \theta_2(t). \tag{16}$$

Note Since the phase representations in Sect. 3.2 yield angular values defined on the circle $[0, 2\pi]$, the phase is unwrapped, i.e., 2π-jumps are removed such that $\Phi \in \mathbb{R}$. The time series $\Phi(t)$ start at the movement onset of the delayed agent and end after completion of ten cycles.

3.3.2 Experimental observation of synchronization

In theory, a coupled oscillatory system is synchronized, if its phase difference stays bounded for all times. However, in our experimental setting, we are obliged to apply a weaker criterion to investigate synchronization due to a limited available observation length of human movements: a thorough trade-off between capturing a potential process of phase convergence and the influence of the participants' fatigue increasing over time has to be made. With an observation length of ten cycles chosen in our experiment, we are able to show that the transient process of synchronization is happening in the first few cycles of the task. The temporal differences between the actions of both agents at key events, such as the time of target entry are decreasing within the first three cycles only (see also Lorenz et al. 2011), which makes a length of ten cycles a reasonable choice.

3.3.3 Quantification with the synchronization index

Numerous approaches on measuring synchronization from time series can be found in literature, see e.g., Kreuz et al. (2007) for a comprehensive comparison. Since the instantaneous phases represent the oscillatory entities in this article, we follow a common approach to quantify phase synchronization: given the time series $\Phi(t)$ consisting of N directional observations $\Phi(t_j)$, directional statistics provides a *synchronization index*

$$SI = \left| \frac{1}{N} \sum_{j=1}^{N} \mathrm{e}^{i\Phi(t_j)} \right| = 1 - \mathrm{CV}, \tag{17}$$

where CV denotes the circular variance of an angular distribution.[2] The synchronization index SI is the length of the mean resultant vector of the phase difference samples $\Phi(t_j)$ transformed into unit vectors in the complex plane.

Note SI lies in the interval [0,1]. Given a perfectly uniform distribution of phase differences, it would equal zero. In perfect synchronization it would equal one, which means that all samples of Φ point to the same direction.

4 Coordination model of the interacting dyad

In this section, we present the steps taken toward a model of interpersonal movement coordination. Starting with an investigation of the experimental data regarding the characteristics of movement synchronization, the model structure is developed and the model parameters are identified.

4.1 Experimental results

In a first step, we elucidate the temporal process leading to synchronization and the phase relations emerging among the partners by plotting the data and analyzing the phase difference.

4.1.1 Patterns of movement synchronization

In our study of human movement behavior in a goal-directed task, we found relations between the movements of dyads which were established over the course of a trial (Lorenz et al. 2011). In order to visualize these findings, a frequency distribution is plotted as a *heat map* of all motion trajectories. Here the movement x_2 of person 2 is represented as a function of the movement x_1 of person 1. For each trial and cycle, the actual position of person 2 is calculated as a function of person 1's position. The resulting curve is sampled with an underlying grid of 100×100 cells and the number of times each cell in the grid is hit by a curve is determined. Those binned counts are plotted for each forward and backwards movement separately into a *heat map* in which brightness codes frequency of cell hits, see Fig. 6. In these plots, perfect in-phase or anti-phase synchrony appear as straight diagonal lines. During in-phase relation, the movements have no phase shift, e.g., if person 1 is in the starting position at 0 m person 2 is there as well. On their way to the target participants are always at the same point in their trajectory. Thus, when dyads are perfectly in-phase during forward movements, a line goes from top left to bottom right. During backwards movements—where the abscissa labeling goes down—the plot shows a straight line from the bottom left to the top right if the interaction partners are perfectly synchronized. In perfect anti-phase, this pattern is mirrored horizontally because when one person is at the start position, the other person is in the target position and vice versa. When participants are not perfectly synchronized, data appear curved. Note that

[2] the synchronization index SI is also called mean phase coherence.

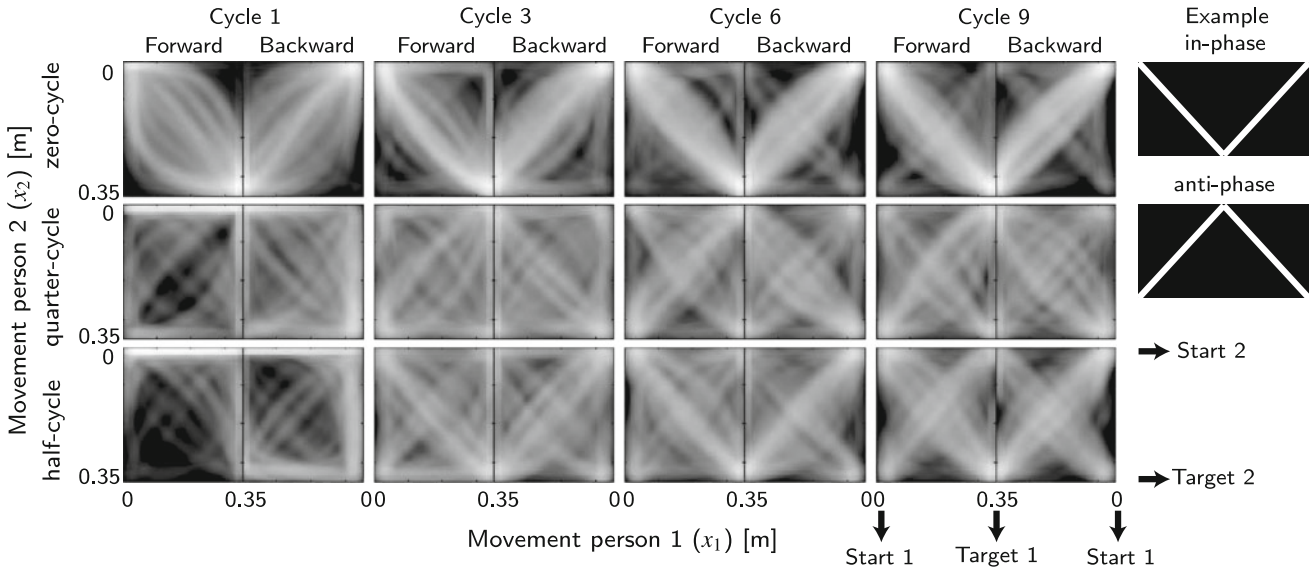

Fig. 6 How did synchrony evolve? This Figure contains frequency distributions (of all trials) of the hand position of person 2 relative to that of person 1 (see also Lorenz et al. 2011). The hand positions are one-dimensional positions between the start (=0 m) and target (=0.35 m). The brighter a location in this picture is, the more often that positional relationship occurred. Relative movements (between the two participants) shown up as *lines*. Perfect in-phase and anti-phase synchrony would be *straight diagonal lines*, see *upper right*. The pictures show that the participants tended to synchronize already early in the trial. Data are plotted separately for the first, third, sixth, and ninth cycles. In the zero condition (*upper panels*), phase relationships already appear like in-phase and anti-phase relationships in the third cycle. In the other two conditions (quarter-cycle in the middle panels and half-cycle conditions in the lower panel) roughly the same happens, but there appear to be slightly stronger and more deviations.

only the in-phase and the anti-phase relations are easy to identify in this graphical representation because they appear as straight lines. Other stable phase relations would show a more complicated pattern and thus cannot be determined as intuitively.

Most importantly, the heat map visualizes that in-phase and anti-phase relationships are already established early in the trial. During the first cycle, data tend to be curved for all conditions. After that, movements are quickly adapted, which is depicted by the curves becoming straighter. Data of the zero-cycle condition show that people are already almost perfectly adapted to each other after performing the third cycle. Straight lines become prevalent indicating in-phase movements. In contrast, during the half-cycle condition, both the in-phase and anti-phase relations are established roughly equally often until the ninth cycle. This is interesting because one might have expected that if starting off at the same time mainly leads to in-phase relations, starting off at opposite positions should mainly lead to anti-phase relations. Roughly the same result is observed for the quarter-cycle condition. The difference to half-cycle is that more curved lines appear during the quarter-cycle condition and constant phase relations are established later there. This indicates that it is more difficult to establish a stable in-phase or anti-phase relation when starting off in an odd temporal ratio.

4.1.2 Characterization of the attractor regimes

In addition to the graphical representation of synchronization in the heat maps, the analysis of the phase difference allows to further characterize the attractive domains of the synchronization process.

Any prevalent phase relation can be made visible by histogram representations of the phase difference time series, see Fig. 7a–c. Since the attractor regime is characterized by the relative phase relation within the dyad, we define the relative phase difference

$$\Phi_r(t) = \begin{cases} |\Phi(t) \bmod 2\pi|, & \text{if } |\Phi(t) \bmod 2\pi| \leq \pi \\ 2\pi - |\Phi(t) \bmod 2\pi|, & \text{otherwise.} \end{cases}$$

The data samples of $\Phi_r(t)$ are assigned to 40 equally spaced bins in $[0, \pi]$ and accumulated over all trials. Distinct peaks at angular values around multiples of π are common to the histograms of the three conditions zero-, quarter-, and half-cycle. They become even sharper if only the second half of each trial is considered where transient processes are nearly completed. Totally uncorrelated phases would cause approximately uniform distributions, whereas perfectly synchronized phases would result in sharp vertical lines. The center values of such peaks can thus be treated as features appropriate for modeling. The width of the peaks is associ-

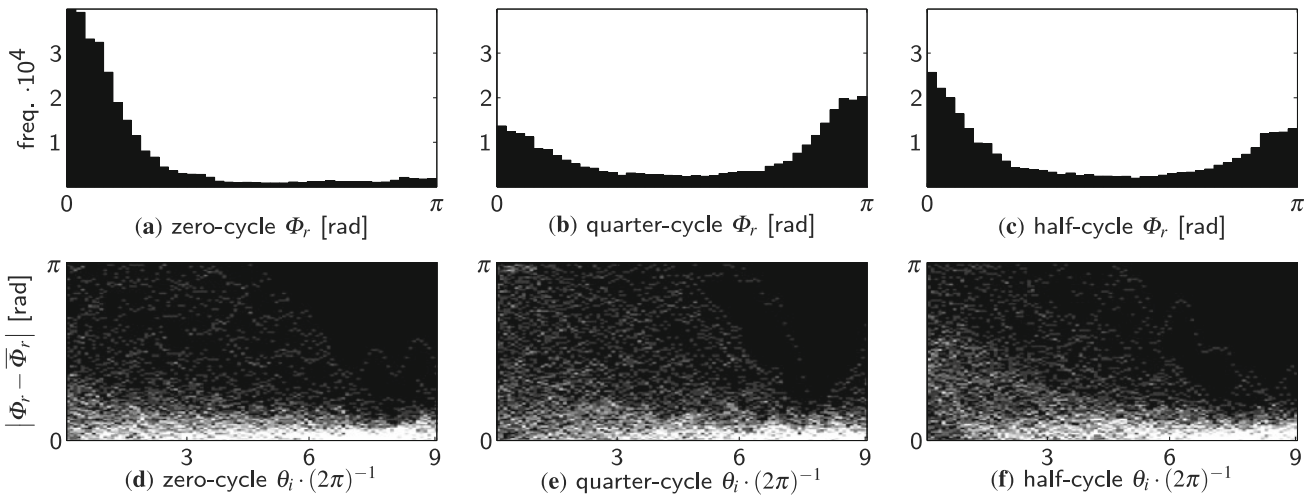

Fig. 7 The histograms (**a**–**c**) of the relative phase difference Φ_r show clear peaks at values around 0 and π, which suggest multiples of π as preferred phase relations or attractors, respectively. The heat maps (**d**–**f**) depict the transient process of the relative phase difference toward its attractor (ordinate), which is indexed by the phase angle of the delayed person θ_i (abscissa). Frequency of the relative phase difference is coded by brightness. The time series of Φ_r and θ_i are generated with the spectral method and accumulated over all trials in the three conditions.

ated with the variance and the synchronization index (17), respectively.

With a closer look at the distributions, it can be stated that in the zero-cycle condition (Fig. 7a) the participants' phase difference predominantly stays in one single regime at $\Phi_r = 0$, which refers to the in-phase relation. Starting off in-phase means attaining an in-phase relation in nearly all of the trials. In the quarter-cycle condition (Fig. 7b), two different attractor regimes become visible: the in-phase attractor but also an attractor at $\Phi_r = \pi$, which refers to the anti-phase relation. Starting off in quarter-cycle leads to both the in-phase and anti-phase relations, while it seems as if the latter was preferred. In condition half-cycle (Fig. 7c), the same attractors as in quarter-cycle appear. Starting off in half-cycle leads to both in-phase and anti-phase relations.

Note that the histograms only show the prevalent relative phase relations *over trials*, which are $\Phi_r = 0$ and $\Phi_r = \pi$. Though two attractors in Fig. 7b, c can be clearly identified, it cannot be determined from the histograms if spontaneous *switches* between them occur *within trials*. Therefore, we investigate the convergence of the relative phase difference $\left|\Phi_r(t) - \overline{\Phi_r}\right|$ as a function of cycles, where

$$\overline{\Phi_r} = \frac{1}{N - \left\lfloor \frac{2N}{3} \right\rfloor + 1} \sum_{j=\left\lfloor \frac{2N}{3} \right\rfloor}^{N} \Phi_r(t_j)$$

denotes the mean of each time series $\Phi_r(t)$ taken over the last third of the total samples N of each trial. The distributions in Fig. 7d–f are nicely aligned around zero between cycle 6 and 9 for most of the trials, which illustrates overall convergence to the preferred attractors. The distributions are scattered between 0 and π up to cycle 6, as an indication of the process of convergence happening in the first few cycles of interaction. No preferred clusters around π can be detected in these distributions. Thus, we can conclude that besides the initial convergent process, within-trial switches between the two preferred attractors rarely take place during the experimental observation length.

Both the heat map representation and the phase difference distribution provide clear evidence of synchronization in our goal-directed experimental task. The process of synchronization is characterized by two attractor points of the relative phase difference, namely the in-phase and the anti-phase relations.

4.1.3 Initial phase difference

Though in the half-cycle condition the dyads are triggered to start of in the anti-phase relation, both the anti-phase and the in-phase attractors can be identified in the histogram (Fig. 7c), with even a prevalence of the latter. For clarification, the actual initial phase difference of each trial is illustrated in Fig. 8. The distribution shows clusters for the different conditions, yet under quarter- and half-cycle with an additional phase delay around π with respect to the phase relation triggered by the respective start off condition. These delays are mainly caused by the participants' reaction and dwell times when engaging jointly in action. Especially in the half-cycle condition, the actual initial phase differences are often close to the in-phase relation, which explains the frequently appearing in-phase attractor in the histogram (Fig. 7c). Due to the simultaneous start off trigger in the zero-cycle condition, the actual initial phase difference is affected less by the delay. In brief, the applied conditions are shown

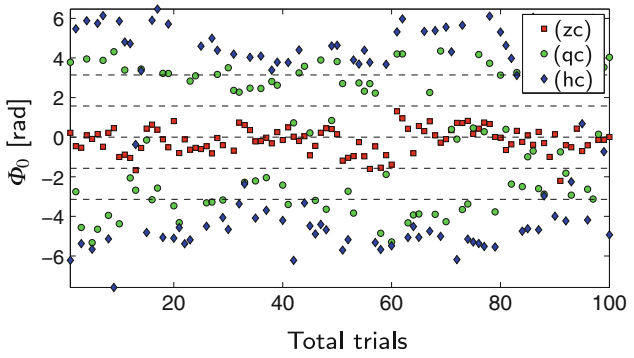

Fig. 8 Actual initial phase differences $\Phi_0 = \Phi(t = 0)$ over trials calculated with the spectral method for the conditions zero-cycle (*zc*), quarter-cycle (*qc*), and half-cycle (*hc*). Time $t = 0$ denotes the movement onset of the delayed person. *Dashed lines* indicate the phase relations triggered by the start off conditions.

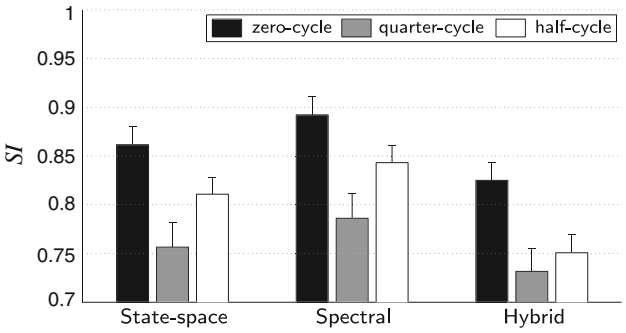

Fig. 9 Synchronization index *SI* for the conditions zero-, quarter- and half-cycle averaged over all trials. For comparison, *SI* is calculated separately for the phases estimated by the state-space, spectral, and hybrid methods. The *bars* represent standard errors of the means.

to effectively trigger a distribution of different initial phase relations, which enables to perform a parameter estimation based on the response dynamics of the dyads.

Note In goal-directed tasks, a leadership among the dyad can be defined when the sign of the phase difference $\Phi = \theta_1 - \theta_2$ is evaluated: person 1's phase θ_1 larger than person 2's phase θ_2 means that person 1 is leading the task by preceding person 2's action and vice versa. The symmetry of Φ_0 observed in Fig. 8 is due to the initial trigger of action start off, which is equally often assigned to each of the partners.

4.1.4 Evaluation of the synchronization index

The synchronization index *SI* given by (17) provides a quantification of synchronization in a single number. Based on the definition that a collective remaining constant over time yields the highest degree of synchronization, the measure penalizes any variability of the collective including, e.g., the transient process when getting synchronized and also transitions between attractors. Therefore, it has to be considered that the choice of the variables constituting the system's collective affects the characteristics of the measure. When looking at the scores of the synchronization index *SI* in Fig. 9, the influence of the method used to estimate the phase variables becomes obvious. A one-way repeated measures ANOVA was performed to assess the difference between *SI*s obtained with the state-space, spectral and hybrid method. As the sphericity criterion was not met, Greenhouse–Geisser correction was applied. *SI*s differed quantitatively, $F(1.2, 34.9) = 66.78$, $p < .001$, which can be explained by a differing sensitivity of the method to the variabilities in the movement profiles. Only the dominating frequency determines the phase of the spectral method ($M = 0.84$), which makes it rather insensitive to small, local movement variabilities. In contrast, such variabilities directly influence the instantaneous phase of both the state-space ($M = 0.81$) and the hybrid methods ($M = 0.77$). The inferior score of the hybrid method suggests that the parameterization of the minimum jerk model chosen as the primitive representation does not perfectly match the movement profiles observed in our experiment.

The indexes given in Fig. 9 consider whole trials including the transient process of synchronization. If the transient process is neglected and the synchronization index is calculated only on the second half of each trial, similar qualitative results can be obtained. In condition zero-cycle, the highest index values are achieved on average. Thus, starting off in zero-cycle enables the partners to reach highest quality of synchronization. Starting off in quarter-cycle yields lowest values due to a rather high phase variability within the dyads, which is in agreement with the distribution Fig. 7b. Medium index values are attained in half-cycle. The resulting indexes show similar trends within methods, yet the one-way repeated measures ANOVAs with the within-subject factor *condition* (zero-, quarter-, and half-cycle) performed for every method did not reveal any significant differences between start off conditions, all $p > .05$. If we interpret the synchronization index as an analytical indication of strength of the involved attractors, it cannot be clearly stated that the attractor strengths of the in-phase and the anti-phase relation differ in our goal-directed experiment. In contrast, research work on interpersonal movement synchronization in purely rhythmic tasks provides evidence of different attractor strengths, i.e., the anti-phase attractor has a strong tendency to be weaker than the in-phase attractor or even disappears (Schmidt and O'Brien 1997; Richardson et al. 2007).

4.2 Modeling approach

The analysis of the phase variables reveals temporal interaction between the partners which is closely related to the definition of phase synchronization. The emerging synchronization effects can be modeled as a synchronization problem

of two mutually coupled oscillators. In a next step toward the coordination model, we set up an adequate model structure and investigate its relevant properties.

4.2.1 Model of two coupled oscillators

First, we recall the general equations of motion of two limit cycle oscillators (1) and (2) that are mutually coupled. Under the assumption that the coupling functions G_i are weak and the oscillatory dynamics are harmonic (Kuramoto 1984), the above equations can be reduced to a simpler set written in terms of the oscillators' phase angles θ_i as

$$\dot{\theta}_1 = \omega_1 + H_1(\theta_2 - \theta_1) \tag{18}$$
$$\dot{\theta}_2 = \omega_2 + H_2(\theta_1 - \theta_2), \tag{19}$$

where ω_i are the natural frequencies of the oscillators and the coupling functions H_i depend on the phase difference between the oscillators.

Note In our modeling approach, the phase $\theta_i(t)$ is assumed to be quasi-harmonic. Harmonicity is either fulfilled due to the harmonic nature of the movements the phase is constructed from or it can be achieved by an appropriate phase transformation, e.g., the hybrid method presented in Sect. 3.2.3.

4.2.2 Extending the Kuramoto model

Several candidates for the coupling functions H_i in (18), (19) have been proposed in the context of movement synchronization. One of them is the sinusoidal function proposed by Rand et al. (1988) which yields the model equations

$$\dot{\theta}_1 = \omega_1 + K \sin(\theta_2 - \theta_1) \tag{20}$$
$$\dot{\theta}_2 = \omega_2 + K \sin(\theta_1 - \theta_2). \tag{21}$$

It is also known as the classical *Kuramoto model* (Kuramoto 1984), where K is the coupling gain between the oscillators. It is assumed to be isotropic for both oscillators. We adopt the model of coupled Kuramoto oscillators for the following reasons:

- Despite its simplicity, the observed main effects of synchronization are replicated: The natural frequencies refer to the agents' individual frequency levels as an individual behavior, whereas the additive nonlinear coupling term allows synchronization between the agents to emerge.
- Emerging synchronization is explained as an effect of co-adaptation with an isotropic bidirectional coupling. Directionality of coupling characteristics would be hard to identify from short-time bivariate data recorded during natural HHI, since unsynchronized regimes have to be observed extensively (Smirnov and Andrzejak 2005).
- The goal-directedness of the task constrains the amplitudes of movements, thus only the quasi-harmonic phases are considered. The two-degrees-of-freedom model fosters parameter identification from noisy data.

The phase difference dynamics between the two oscillators are obtained by subtracting (21) from (20) and can be compactly written as

$$\dot{\Phi} = \Delta\omega - 2K \sin \Phi, \tag{22}$$

with $\dot{\Phi} = \dot{\theta}_1 - \dot{\theta}_2$ and the frequency detuning

$$\Delta\omega = \omega_1 - \omega_2. \tag{23}$$

The analytical results from Sect. 4.1 show that the phase relation between the interacting agents ends up predominantly either in in-phase ($\Phi = 0$) or in anti-phase ($\Phi = \pi$). Therefore, we extend the phase difference dynamics (22) by two additional equilibrium points per period of Φ, which yields the differential equation of the phase difference

$$\dot{\Phi} = h(\Phi) = \Delta\omega - 2K \sin(2\Phi) \tag{24}$$

with the model equations

$$\dot{\theta}_1 = \omega_1 + K \sin\left[2\left(\theta_2 - \theta_1\right)\right] \tag{25}$$
$$\dot{\theta}_2 = \omega_2 + K \sin\left[2\left(\theta_1 - \theta_2\right)\right], \tag{26}$$

called the extended Kuramoto model in the following.

4.2.3 Stability analysis

Next, the stability of the equilibrium points of the extended Kuramoto model (24) is investigated. Setting $\dot{\Phi} = 0$, one obtains

$$2K \sin\left(2\Phi_e\right) = \Delta\omega. \tag{27}$$

The equilibrium points Φ_e are then given by the solutions of (27) or graphically represented, by the points of intersection of the curves $2K \sin(2\Phi)$ and $\Delta\omega$, see Fig. 10.

Note Equilibrium points Φ_e, i.e., solutions of (27) exist, if the parameter set $(\Delta\omega, K)$ satisfies the inequality

$$|\Delta\omega| - 2\,|K| < 0. \tag{28}$$

Let $\eta = \Phi - \Phi_e$ be a small perturbation away from Φ_e. In order to analyze the stability of the equilibrium points, we investigate whether the perturbation grows or decays. First, we derive a differential equation for η given by

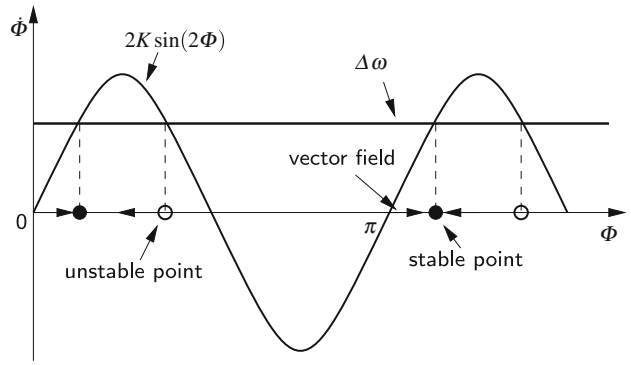

Fig. 10 Stability of the equilibrium points of the extended Kuramoto model. The phase difference between the two oscillators converges close to 0 (in-phase) or π (anti-phase) depending on the strength of coupling K and the frequency detuning $\Delta\omega$.

$$\dot{\eta} = \frac{\mathrm{d}}{\mathrm{d}t}(\Phi - \Phi_\mathrm{e}) = \dot{\Phi} = h(\Phi_\mathrm{e} + \eta).$$

Using Taylor's expansion and noting that $h(\Phi_\mathrm{e}) = 0$ one gets

$$\dot{\eta} = \eta h'(\Phi_\mathrm{e}) + O(\eta^2),$$

where $O(\eta^2)$ gathers quadratically small terms in η. The gradient

$$h'(\Phi_\mathrm{e}) = \frac{\mathrm{d}}{\mathrm{d}\Phi} h|_{\Phi=\Phi_\mathrm{e}} = -4K\cos(2\Phi_\mathrm{e}) \tag{29}$$

denotes the *attractor strength* of Φ_e. If $h'(\Phi_\mathrm{e}) \neq 0$, the approximation can be written as

$$\dot{\eta} = \eta h'(\Phi_\mathrm{e}). \tag{30}$$

It can be seen from (30) that the perturbation η grows exponentially, i.e., the equilibrium Φ_e is unstable if $h'(\Phi_\mathrm{e}) > 0$ and decays, i.e., Φ_e is stable if $h'(\Phi_\mathrm{e}) < 0$. The stability analysis can be visualized by investigating the dynamics of the vector field on the abscissa as shown in Fig. 10, where the solid and open dots represent the stable and unstable equilibrium points, respectively. Two stable and two unstable equilibrium points exist per period of Φ. The attractor strength $h'(\Phi_\mathrm{e})$ given by (29) depends not only on the coupling gain K but also on the frequency detuning $\Delta\omega$, which shifts Φ_e. Growing/decaying values of $\Delta\omega$ move the stable equilibrium points in the positive/negative direction along the abscissa; i.e., the model explains a positive/negative shift of the steady-state phase difference by a positive/negative frequency detuning among the dyad.

Note The stable equilibrium points around $\Phi = 0, \pi$ have the same attractor strength and therefore equal stability properties due to the 2π-periodicity of (29). The model structure is chosen, since the analysis of the data gathered in our experimental paradigm does not provide clear evidence for attractor switches or different attractor strengths in our goal-directed task. The extended Kuramoto model can be modified to address different attractor strengths, yielding the phase difference dynamics

$$\dot{\Phi} = \Delta\omega - 2K\sin(2\Phi) - 2K_0\sin(\Phi)$$

with an additional sine term and coupling parameter K_0, which is obviously the HKB model structure extended for different eigenfrequencies (Haken et al. 1985; Fuchs and Kelso 1994).

4.2.4 Natural frequencies of the oscillators

Investigation of the relation between the frequency detuning $\Delta\omega$ and the equilibrium frequency ω_e of the coupled oscillators in the extended Kuramoto model allows us to derive the natural frequencies ω_i, which describe the uncoupled oscillators. In equilibrium, we can write

$$\dot{\Phi} = \dot{\theta}_1 - \dot{\theta}_2 = 0,$$

which is satisfied for the frequency

$$\omega_e = \dot{\theta}_1 = \dot{\theta}_2. \tag{31}$$

The frequency ω_e is the common frequency during synchronized regimes and can be determined through measurement. Plugging (31) into the model equations (25), (26) and applying (23) yields

$$\omega_{1,2} = \omega_e \pm \frac{1}{2}\Delta\omega.$$

Thus, ω_e is the mean of ω_1 and ω_2, which is a common property of the Kuramoto model. The natural frequency ω_i predict agent i's individually preferred cycle frequency, which is assumed to be a constant parameter within the joint action context. When modeling human motor behavior, the individual cycle frequencies predicted by the model have to be interpreted carefully; it is known for example that working speeds differ when humans perform a motor task alone and jointly with others (see e.g., Vesper et al. 2009).

4.3 Parameter identification

In the following, the requirements and technique to obtain the parameter values $(\Delta\omega, K)$ of the model structure and the results of the parameter identification are presented.

4.3.1 Observation of the natural response dynamics

A general requirement for a successful parameter identification is the perturbation of the system and the observation of the system's response, which can be achieved either by an externally applied excitation or by an initial perturbation of the system from its equilibrium. The latter provokes the system's *natural response dynamics*; e.g., when a pendulum is

pulled back from its equilibrium state and released in a different initial state, its natural frequency can be determined by measuring the frequency it swings at. Since any externally applied excitations such as enforcing frequencies or an imposed frequency detuning (Schmidt et al. 1998) could hinder natural HHI, we decided not to actively control the interaction of the partners during our experiment, rather to observe it. Thus, the experiment can be classified as *passive*, which includes that parameters of the system cannot be changed and only bivariate data are available (see also Pikovsky et al. 2001). With our experimental design, the idea is to trigger different initial phase differences $\Phi_0 = \Phi(t = 0)$ (c.f. Fig. 8). The dyad's natural response to the applied start off conditions in the experiment serves then for the identification of the parameter sets.

Note If the frequency detuning $\Delta\omega$ within the interacting system is known, e.g., the eigenfrequencies of oscillatory mechanical systems can be controlled, the coupling strength K could be alternatively identified from the phase difference Φ_e during equilibrium $\dot{\Phi} = 0$ observed for different values of $\Delta\omega$ via the regression method of Schmidt et al. (1998).

4.3.2 Estimation of the model parameters

The model structure which is given by the nonlinear dynamical equation (24) and the time series of the phase difference $\Phi(t)$ enables an estimation of the parameters $(\Delta\omega, K)$ for each trial. The estimation problem is solved with the iterative prediction-error minimization method (PEM), which minimizes an error objective function depending on the simulated model output and the time series data (Ljung 1999). A so-called gray box model which implements (24) is fed into the PEM-algorithm of MATLAB's System Identification Toolbox and the initial state of the model is estimated jointly with the parameter set to achieve best fitting. Both the time series data of the analytically derived phase difference and the simulated model output after the parameter estimation are illustrated for a representative trial in Fig. 11. The dynamics of the trial investigated here are judged to be stable according to (28), hence the simulated phase difference converges to the attractor point close to π. Possible reasons for the oscillatory phase fluctuations (c.f. Fig. 11) present in most of the trials are discussed in Sect. 5.

4.3.3 Results of the parameter estimation

For comparison, the model parameters estimated for phase difference time series acquired with the state-space, spectral and hybrid methods are summarized in Table 1. Since the transformation of motion trajectories to phases is not unique but based on certain assumptions as introduced in Sect. 3.2, the applied method affects the modeling results and makes

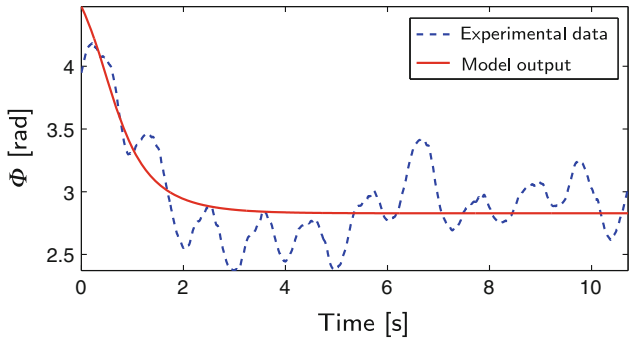

Fig. 11 Comparison of the phase differences $\Phi(t)$ analytically derived with the spectral method and simulated with the parameterized model. The parameters [rad s^{-1}] of the trial are $\Delta\omega = -0.49$ and $K = 0.41$ at an RMSE = 0.23.

it part of the modeling approach. More than two-thirds of the trials yield parameter sets with stable point attractors of the resulting dynamical system according to the stability criterion (28). Thus, it can be stated that the synchronization effects visible in Figs. 6 and 7 are reproduced by stable parameter sets in a majority of the trials.

For statistical analysis of the obtained results, one-way repeated measures ANOVAs with the within-subject factor *method* (spectral, hybrid, state-space) were performed. In order to compare the methods, data were averaged over start off conditions. Greenhouse–Geisser correction was applied when the sphericity criterion was not met. The influence of the unstable parameter sets on the overall coupling gain is rather small; if only the trials are considered, in which the partners synchronize according to (28), the coupling gain (denoted with $|K_s|$ in Table 1) is not much higher than $|K|$. In both cases, a significant main effect between methods is observed, $|K|$: $F(2, 18) = 3.87$, $p < .05$, $|K_s|$: $F(2, 18) = 3.88$, $p < .05$. Contrasts show that the spectral method results in the smallest coupling gain on average compared to both the hybrid, $|K|$: $F(1, 9) = 8.37$, $p < .05$, $|K_s|$: $F(1, 9) = 6.09$, $p < .05$, and the state-space method $|K|$: $F(1, 9) = 7.15$, $p < .05$, $|K_s|$: $F(1, 9) = 7.50$, $p < .05$, with the latter not being different from each other. This illustrates that the commonly detected synchronization effects are explained by a non-zero coupling term, though no instructions are given which actively modulate the interaction in the experiment.

A mean $\Delta\omega$ close to zero indicates a rather balanced frequency detuning over all dyads. No significant differences between methods are found, $p > .6$. However, a small negative component of $\Delta\omega$ points to the trend that the individual cycle frequency preferred by person 2 is on average slightly higher than person 1's frequency. The considerably high SD $\Delta\omega$ leads to the conclusion that the frequency detuning predicted by the model is an individually varying parameter.

Table 1 Estimated model parameters, RMSE assessing model fit, and number of trials N_{stable} with stable parameter sets

Method	Mean $\lvert K\rvert$	SD $\lvert K\rvert$	Mean $\lvert K_s\rvert$	Mean $\Delta\omega$	SD $\Delta\omega$	Mean RMSE	N_{stable}
State-space	0.29	0.14	0.34	−0.08	0.19	0.41	218
Spectral	0.20	0.05	0.24	−0.06	0.14	0.26	223
Hybrid	0.29	0.11	0.33	−0.09	0.15	0.59	202

Means are taken over $N_{\text{valid}} = 294$ trials. SDs are taken over dyads. The results [rad s^{-1}] are presented separately for the state-space, spectral, and hybrid methods

Table 2 Results of the trial-wise regression

Method	Condition	Median R^2	N_{valid}	$N_{p<.001}$
State-space	Zero-cycle	0.313	98	98
	Quarter-cycle	0.994	97	97
	Half-cycle	0.996	99	99
Spectral	Zero-cycle	0.350	98	97
	Quarter-cycle	0.971	97	96
	Half-cycle	0.998	99	99
Hybrid	Zero-cycle	0.223	98	98
	Quarter-cycle	0.904	97	97
	Half-cycle	0.995	99	99

R^2 represents the percentage of the variance explained by the model, N_{valid} is the number of valid trials which were included into analysis for the respective condition and $N_{p<.001}$ list how many times the model fit is above chance (at $p < 0.001$)

4.3.4 Evaluation of the model fit

For comparison of the root-mean-square-error of model prediction and measurement (RMSE in Table 1) a one-way repeated measures ANOVA with the within-subject factor *method* (spectral, hybrid, state-space) was performed. Degrees of freedom were corrected with the Greenhouse–Geisser method. Here, highly significant differences between methods are observed, $F(1.1, 9.7) = 28.37$, $p < .001$. Best model fit is achieved by the combination of the extended Kuramoto model and the spectral method. It differs significantly from the RMSE obtained with the state-space method, $F(1, 9) = 167.47$, $p < .001$, or the hybrid method, $F(1, 9) = 38.53$, $p < .001$. Furthermore, RMSE is lower with the state-space than with the hybrid approach, $F(1, 9) = 11.20$, $p < .01$. This is due to the filtering property of the Hilbert transform, as the frequency at the maximum of the power spectrum determines the instantaneous frequency and phase, respectively. Both the state-space and hybrid methods are applied without any filtering technique and thus yield a higher phase variability than the spectral method, which is not explained by the model.

In addition, the model's goodness of fit in combination with the three phase estimation methods is assessed with the R-square metric (R^2), which allows for an estimation of how much variance of the data (in %) are explained by the respective model. The median values of the trial-wise R^2 are summarized in Table 2. In order to find out how often the variance of the data is explained above chance level, the significance of each trial's model fit is tested by calculating the F-ratio. The numbers of significant fits are reported in Table 2.

5 Discussion

Both the results from data analysis and model synthesis provide evidence for and characterize the emerging synchronization of movements. Treating human dyadic interaction in a repetitive, goal-directed task as a synchronization problem with the phase difference of coupled oscillators as the collective seems to be a valid approach. Its implications are discussed in the following.

5.1 Performance comparison of the phase transformations

Three different methods on the calculation of instantaneous phases from experimental movement data are evaluated in this study. Their performance is assessed by (1) looking at the synchronization index, which penalizes the phase variability and (2) the RMSE, which accounts for the residuals after model identification. When comparing the values of the synchronization index and the RMSE-based model fit, both measures yield similar performance trends between the methods on phase transformation. This similarity can be explained by the following fact: the proposed model structure replicates the dominant process of phase convergence only, and therefore in the model residuals any additional variance of the collective becomes directly visible, which affects both the RMSE and the synchronization index in the same way. Best performance results are achieved when the phases are generated by the spectral method. While it is a powerful tool when it comes to off-line analysis, the spectral method is less suitable for on-line application, since a short-time implementation of the Hilbert transform would be required, at the cost of signal delay. For movement tasks comprised by a quasi-harmonic action sequence, where a

state-space can be defined and its state variables can be measured, the state-space method is a good alternative, which can be also deployed on-line. The concept of the hybrid method is superior to both the state-space and the spectral methods, if the phase of arbitrary complex, non-harmonic primitive sequences is to be estimated on-line. When applied to the experimental dataset, the performance of the hybrid method is inferior to the state-space and the spectral methods in its current implementation. It has to be remarked that task knowledge is encoded by the mathematical representations (8) and their transitions induced by the segmentation. Both are not unique but affect the resulting performance of the approach. There are other representations than the minimum jerk model introduced as an approximation of the movement primitives in our experiment: e.g., for perfect harmonic movements, results equivalent to the state-space method could be obtained when the action sequence is segmented into two movement primitives, each represented by a trigonometric function. Enhancing the segmentation of the action sequence by predictive parameterizations as well as improving the primitives' mathematical representations by estimation techniques with subsequent evaluations of the hybrid method in complex movement tasks is a promising way to extend the power of the coordination model.

5.2 Interpretation of the model residuals

The extended Kuramoto model predicts only the dominant component of the collective's dynamics by a first-order nonlinear dynamical system. The median R^2 under condition zero-cycle is remarkably low regardless of the method. Since the measured phase difference remains constantly close to the attractor $\Phi = 0$ for most of the zero-cycle trials, the explanatory power of the extended Kuramoto model in these trials does not exceed much that of the pure mean value of the measured phase difference. Potential additional information content might be present in the model residuals. Through a spectral analysis of the residuals, oscillatory components at frequencies close to the participants' cycle frequencies ($M = 0.73$ Hz over all trials) can be discovered in many of the trials (c.f. Fig. 11), which is in line with the observations made by Schmidt et al. (1993) during pendulum swinging. These oscillations can be explained by the following reasons.

First and foremost, the observed phase fluctuations can be artifacts of the phase estimation. The instantaneous phase of arbitrary oscillatory time series such as human movement trajectories can be uniquely determined only over cycles for a discrete event in the cycle, while the evolution within cycles strongly depends on the reconstruction method. Neither the movement trajectories of the individuals are purely harmonic nor the phase estimation techniques achieve perfect harmonic phases. Thus, the state-space plots are not perfectly circular but slightly distorted, see Fig. 4. Even if we assume equally distorted state-space plots for both partners, the phase difference $\Phi(t)$ will oscillate at multiples of the cycle frequency for $\Phi(t) \neq 0$. In their note on coordination models, Fuchs and Kelso (1994) show that these phase fluctuations can be reproduced by the original HKB model comprised by non-harmonic oscillators. Within our modeling approach, this effect can be accounted for by further development of the phase estimation techniques with better harmonicity, which is also a prerequisite if more complex goal-directed tasks should be addressed.

Second, the coupling strength between the agents might not be constant over time but rather include components depending on the individual phase. This assumption is backed by the workspace topology of the experimental task investigated here. Since simultaneous visual attention to one's own and the opponent's movement is easier when getting close to the target area and the partner's workspace respectively, it might effect a stronger coupling strength. The integrative role of the visual perception of relative phase has been shown by Wilson et al. (2005); it affects the stability of coordination.

5.3 Interpretation of the modeling results

In most of the trials, participants fall into rhythmic patterns to synchronize. This shows that joint behavior is emerging although the partner's individual goal was to precisely hit the targets. Since experimental results might be strongly task-dependent, we put special emphasis on the design of the task paradigm. The experimental setting is natural in the sense of bearing similarity to repetitive, goal-oriented action tasks. People are not instructed to synchronize, but only get an instruction required for the individual task performance, which allowed natural interaction to emerge. Besides the start off condition, we did not introduce any control variables that artificially modulate the flow of interaction. This should allow an interpretation of the results in the light of natural HHI.

As a result of the system identification, values of the parameter set $(\Delta\omega, K)$ are found per trial. Within our modeling approach, the parameters are assumed to be time-invariant on a short-time scale, i.e., over the course of one experimental trial. The parameter sets averaged over trials can be treated as behavioral features of the dyads. However, accidental as well as deliberate parameter variations might be present due to both environmental influences and intrinsic changes of human behavior.

The frequency detuning $\Delta\omega$ expresses shifts of the equilibrium points to which the collective is attracted. It can serve as a measure of discrepancy regarding the agents' individually desired cycle frequency in the joint action task. Furthermore, hypothetical natural frequencies of the agents can be determined. Their meaning might extend to the self-organi-

zation of leader and follower roles during movement coordination, which deserves further investigation in the light of role behavior among the agents.

The coupling gain K quantifies a dyad's weighing of two potentially competing goals: just being precise to fulfill the instructed goal versus being synchronized with the partner as an additional, voluntary goal. Non-zero mean values of K averaged over all trials indicate emerging interaction between the partners which leads to the observed patterns of synchronization. The regression model employed by Schmidt et al. (1998) to measure coupling strength and the extended Kuramoto model proposed in this article are locally identical, hence the resulting coupling from both task paradigms can be related to each other. The overall mean[3] of $2\,|K|$ ($0.52\,\mathrm{rad}\cdot\mathrm{s}^{-1}$) in Table 1 is about one-third of the mean value ($1.70\,\mathrm{rad}\cdot\mathrm{s}^{-1}$) reported by Schmidt et al. (1998) for the local model coupling strength of (intentional) interpersonal coordination. Since in their experiments, the participants were instructed to swing pendulums either in in-phase or anti-phase relation, a coupling stronger than in our setting could be expected.

6 Conclusion

In this article, we present a step-wise approach to a model of inter-human movement coordination. Motion trajectories were recorded in a novel HHI-experiment which successfully integrates repetitive and goal-directed action. Synchronization is found to be an essential principle of human movement coordination during goal-directed action. The human dyads which participated in our study synchronized their movements. Governed by a dynamical process they fell into in-phase as well as anti-phase relations for most of the trials. The emerging relations are successfully replicated by the attractor dynamics of coupled phase oscillators inspired by the Kuramoto model, which is an oscillator model described by the evolution of its phases. Three different methods on transforming the movement trajectories into instantaneous phases are investigated; closest fitting between experimental data and the model is achieved by the spectral method, which is well-suited only for the off-line analysis of simple repetitive actions. While the state-space method extends the phase estimation to on-line application, the concept of a novel hybrid method is introduced, which allows to derive instantaneous phases for arbitrary complex action sequences. Using a technique that does not influence natural HHI, system identification is performed to estimate the model parameters, which are the coupling strength and the frequency detuning among the dyad. Stable attractor points resulting from the identified model match the relations observed in the experimental data.

The presented approach based on coupled phase dynamics facilitates the modeling of the partners' interactive behavior even when they are engaged in heterogeneous action tasks. The identified model can be readily used to generate the actions of a robotic agent on-line. In a follow-up study, we will deploy the model to an anthropomorphic robot, in order to answer the question: Does a model of inter-human movement coordination enhance human–robot interaction?

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Experiment

Participants

In total, 20 people (13 male, 7 female) participated in the experiment forming 10 dyads. They were between 18 and 28 years old (M = 23.5). All were right handed, had normal or corrected-to-normal vision and were naïve as to the purpose of the experiment. For participation, they were paid 8 per hour.

Experimental Setup

Participants were sitting face to face at a round table on which four circles were marked in two different colors, see Fig. 12. Each color was assigned to one person who was equipped with a marking pen of equal type and size in the respective color. Participants had to hold the pens in their right hands forming a fist around them with the thumb pointing upwards. With this it was achieved that the pen was always in a orthogonal relation to the table surface. We encouraged participants to sit in an upright position and instructed them to put the left hand on their lap. To reduce tapping sound, pieces of felt were attached to the pen tips.

During task performance, participants' hand movements were captured with an infrared 3D-motion tracking system (PTI VisualEyez II VZ4000) at a sampling rate of 30 Hz for acoustical signal triggering and at a sampling rate of 200 Hz for data analysis. LED markers used for motion capturing were attached to the top end of the pen and to the participants' basis thumb joint. Both participants had to wear a pair of stereophones (SONY MDR-XD200) used to present an individual acoustic trigger signal. For being able to review task performance later, hand movements were additionally recorded by a video camera.

[3] Values of K have to be doubled for comparison, since K refers to the single agent's unilateral coupling in our work.

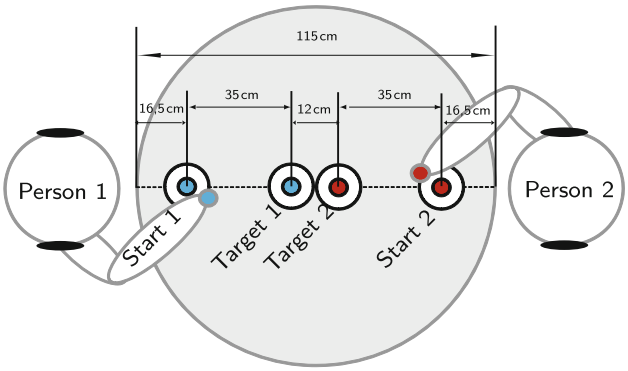

Fig. 12 Experimental setup with dimensions. Two agents denoted as person 1 and person 2 performed identical motor tasks while sitting in chairs and facing each other. The task was to alternately tap on two assigned dots (start and target, diameter 8 mm) with a pen in hand. The *dots* were marked on a round table and each one was surrounded by a *white area* (diameter 60 mm).

Procedure and Design

The experiment started with capturing the individual calibration positions for each dyad. For this purpose, participants had to put their pen to their individual start and target point one time, respectively. The written instruction included a description of the task which was to alternately tap the individual start and target point with the pen tip. Furthermore, participants were asked to carry the pen from one point to the other. Sliding the pen over the table was not allowed. No instructions were given regarding speed in order to provoke natural behavior.

At the beginning of each trial, participants were asked to rest in their respective start position and instructed to start executing the task as soon as they heard the acoustical start signal (high-pitched tone) through their phones. Simultaneously with the start signal, motion capturing started. The stop signal (low-pitched tone) was presented automatically after both participants had performed at least ten cycles each. At the same time, motion capturing stopped and participants had to move their pen back to the start point.

Three start off conditions were applied which provoked differing spatial relations: (1) the start signals for both participants were presented simultaneously (zero-cycle), (2) the start signal for the second person was presented when the first person has already made half the distance between the start and the target point for the first time (quarter-cycle), (3) the start signal for the second person was presented when the first person had reached the target point for the first time (half-cycle). Six sets each consisting of six trials were performed which led to a total of 36 trials. Start off conditions were kept constant within sets which led to a total of 12 trials per condition. In the conditions quarter-cycle and half-cycle, the delay of the start signal for the second person was calculated on-line from the movement data of the first person. Being first person was randomly assigned to person 1 or person 2 and counterbalanced in each set. The first trial in each set was excluded from analysis.

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7.3 APPLICATION IN HUMAN-ROBOT INTERACTION

In order to get a first insight into how the model would enable human-robot movement synchronization, it was implemented to the robot and the goal-directed tapping experiment was repeated. In the following the general outline of the so far unpublished experiment is provided and a first qualitative analysis of the data is given.

7.3.1 *Participants*

Overall, 12 people (7female) took part in the experiments. They were between 21 and 39 years old (M = 26.7years) and received 8 Eur/h for their participation.

7.3.2 *Setup and Procedure*

For this preliminary experiment, the setup and procedure were as described in Chapter 3 and thus similar to the experiments performed before. Tracking and recording the motions of the humans with the PTI Visualeyes Motion Tracker allowed for an online derivation of the humans instantaneous movement phase by using the state-space approach as described in the published paper (Mörtl et al., 2012).

The robot's individual behavior with regard to the task progress is represented by a self-sustained phase oscillator with a constant natural frequency of 0.56Hz. In order to allow for synchronization between the robot's phase oscillator and the observed phase of the human partner to emerge, the adaptation of the robot is realized by means of a coupling gain K which was chosen as the independent variable in five levels:

- K1 = 0 (non-adaptive)
- K2 = 0.25rad/s
- K3 = 0.5rad/s
- K4 = 0.75rad/s
- K5 = 1.0rad/s

Besides capturing movement data, after the experiment participants were asked

1. if they had the feeling that the robot reacted to their movements (Y/N);
2. if yes, then in which way;
3. if yes, how they felt with it.

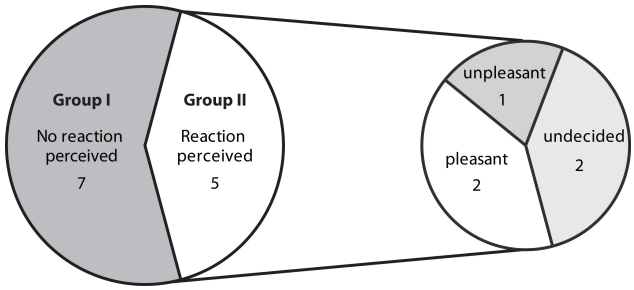
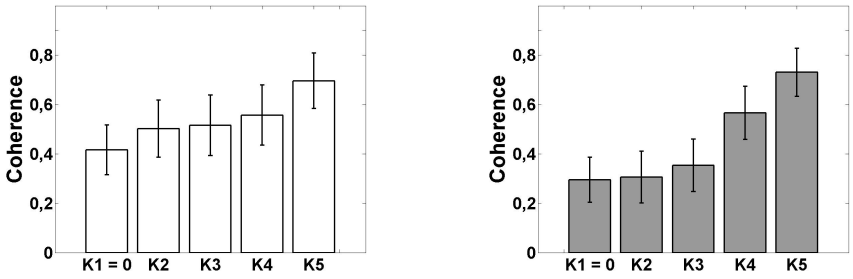


Figure 3: Answers two questions: (1) Did you have the feeling that the robot reacted to your movements? and (3) If yes: how did you feel with it? Numbers are number of participants.



(a) Group I (N)

(b) Group II (Y)

Figure 4: Cross-spectral coherence for human-robot interaction if the huamn a) *did not* (N) b) *did* (Y) recognize the coupling.

7.3.3 *Data Analysis and Qualitative Results*

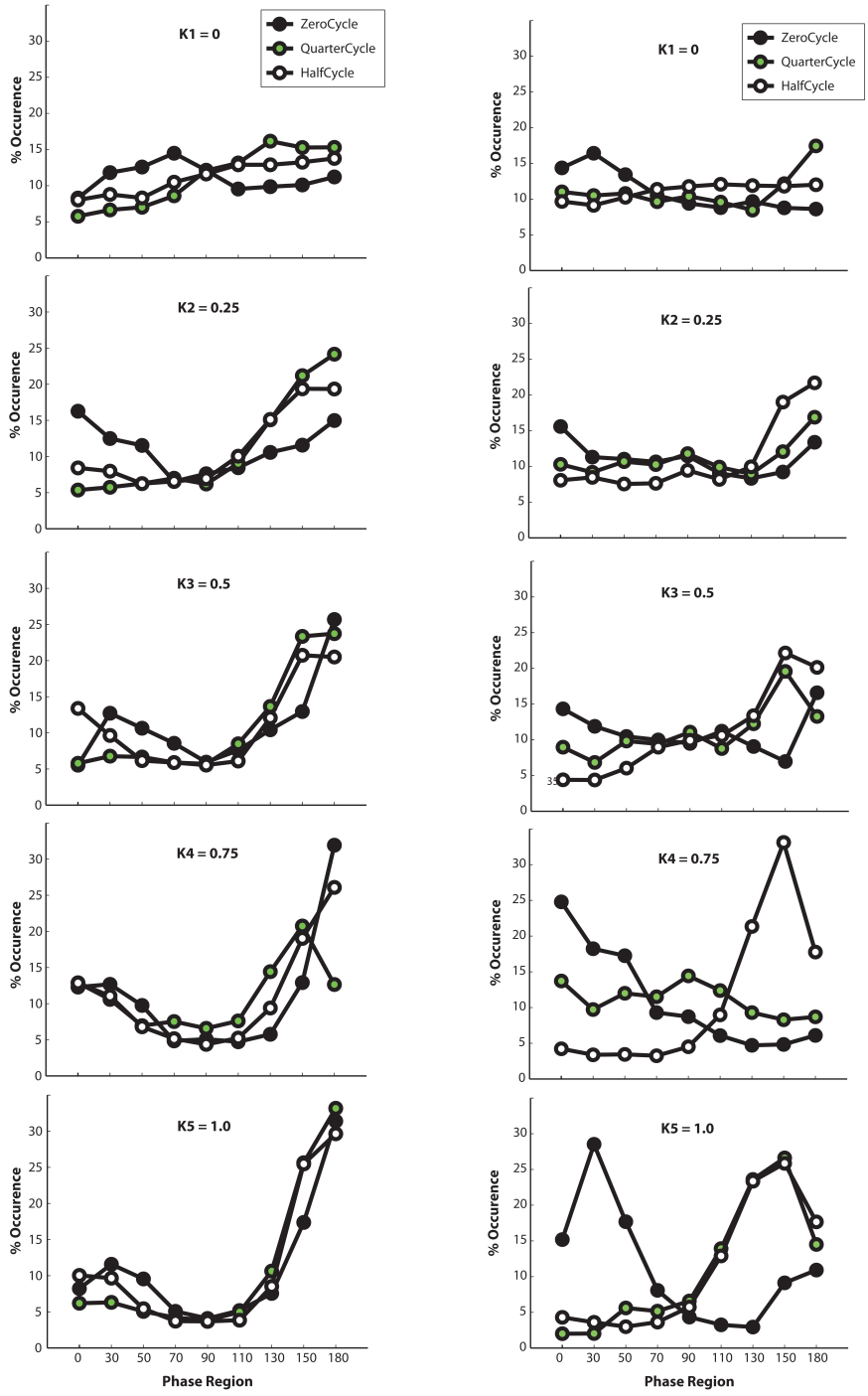
Answers to question 1) and 3) are displayed in Figure 3. Answers to question 2) can be summarized into the perception that the robot "followed my movements" or "adapted to my velocity".

Following the answers to question (1), the further analysis of the movement data was divided into two groups:

- Group I (N): participants who did *not* recognize the coupling
- Group II (Y): participants who *did* recognize the coupling

In each group the cross spectral coherence and the relative phase distribution was calculated, separately for each start delay and coupling gain, see Figures 4 and 5.

If the coupling gain is zero, no synchronization emerges in both cases as expressed by horizontal lines in the relative phase distribution depicted in Figure 5, K1 = 0. However, as can be seen in the comparison of Figure 5a and Figure 5b, the distribution of relative phase results yields distinct patterns for Group I and II with increasing coupling gain. If the coupling was not perceived (Group I (N), Figure 5a), movement synchronization emerges with a tendency for



(a) Group I (N) (b) Group II (Y)

Figure 5: Distribution of relative phase for human-robot interaction if the human a) *did not* b) *did* recognize the coupling, 'HHI' shows the distribution of relative phase obtained from the human-human experiment reported in Chapter 4 for comparison.

anti-phase synchronization, which might be owed to the appearance of the robot (cf. Section 9.1) and the natural tendency to keep distance to it, seeSection 9.1. However if the coupling was perceived (Group II (Y), Figure 5b), rather arbitrary behavior can be observed. It seems that participants declined the robot's adaptation in the lower levels which is also reflected in a rather low coherence in comparison to the group who did not perceive the coupling. Revisiting video tapes of the experiment it becomes evident that the participants who perceived the robots' coupling behavior checked-out the robot's capabilities by trying different movement speeds and accelerations.

Note however that each individual group size is not big enough for a valid analysis, thus the reported results are only qualitative and preliminary. Nevertheless they shed first light on an interesting aspect with regard to human-robot movement synchronization, namely that even if the robot's adaptation is determined by the coupling gain, the amount of the coupling remains an adjustable factor.

8

COMBINING DYNAMIC AND EVENT-BASED MODELING

Life is and will ever remain an equation incapable of solution,
but it contains certain known factors.

— Nikola Tesla

8.1 SUMMARY & CONTEXT

In the previous Chapters it was shown that humans need mutual adaptation to engage in movement synchronization. However it also seems that due to the nature of the goal-directed task, the adaptation is flexibly depending on behavior on different motion primitives, namely in dwelling and moving periods, see Chapter 6. These motion primitives are defined by their temporal duration which can be captured by the time they start and end. Transferred to task performance, these *events* are captured by the contact to the table surface, i.e. the tap and its release respectively. As briefly outlined in Section 1.2.2, these events seem to be relevant for successful coordination.

Thus, in this Chapter the model from Chapter 7 is generalized to capture both principles in a hybrid vein and to enable the design of synchronization behavior for robotic agents in a wide range of tasks. Here, goal-directed tasks are again described by closed movement trajectories following the dynamical systems approach. The current approach however allows to divide these closed trajectories into different motion primitive, segmentable by contact events. Based on oscillator theory, limit cycle representations of the motion primitive trajectories in state space are used to derive the phase variable.

This generalization also includes that different synchronization modes within groups of limit cycles are synthesized considering both continuous phases and discrete events from a unifying point of view. In line with the behavioral dynamics perspective (see Section 1.2 and Section 1.4.2), a dynamical process is designed to synchronize the derived modes.

After an implementation of the provided model on the robot (Section 3.4), a human-robot interaction experiment is described which serves as proof of concept and additionally defines a versatile testbed for the investigation of human-robot interactive behavior in a realistic pick-and-place tasks.

8.2 REFERENCE & CONTRIBUTION

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Conceived and designed the experiments: Alexander Mörtl, Tamara Lorenz, Sandra Hirche. Performed the experiments: Alexander Mörtl, Tamara Lorenz. Analyzed the data: Alexander Mörtl, Tamara Lorenz. Wrote the paper: Alexander Mörtl, Tamara Lorenz, Sandra Hirche

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Rhythm Patterns Interaction - Synchronization Behavior for Human-Robot Joint Action

Alexander Mörtl[1]*, **Tamara Lorenz**[1,2], **Sandra Hirche**[1]

1 Institute for Information-Oriented Control, Technische Universität München, Munich, Germany, **2** Experimental Psychology, Ludwig-Maximilians-Universität, Munich, Germany

Abstract

Interactive behavior among humans is governed by the dynamics of movement synchronization in a variety of repetitive tasks. This requires the interaction partners to perform for example rhythmic limb swinging or even goal-directed arm movements. Inspired by that essential feature of human interaction, we present a novel concept and design methodology to synthesize goal-directed synchronization behavior for robotic agents in repetitive joint action tasks. The agents' tasks are described by closed movement trajectories and interpreted as limit cycles, for which instantaneous phase variables are derived based on oscillator theory. Events segmenting the trajectories into multiple primitives are introduced as anchoring points for enhanced synchronization modes. Utilizing both continuous phases and discrete events in a unifying view, we design a continuous dynamical process synchronizing the derived modes. Inverse to the derivation of phases, we also address the generation of goal-directed movements from the behavioral dynamics. The developed concept is implemented to an anthropomorphic robot. For evaluation of the concept an experiment is designed and conducted in which the robot performs a prototypical pick-and-place task jointly with human partners. The effectiveness of the designed behavior is successfully evidenced by objective measures of phase and event synchronization. Feedback gathered from the participants of our exploratory study suggests a subjectively pleasant sense of interaction created by the interactive behavior. The results highlight potential applications of the synchronization concept both in motor coordination among robotic agents and in enhanced social interaction between humanoid agents and humans.

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* E-mail: moertl@tum.de

Introduction

Synchronization is frequently observed across different modalities and situations. In particular, the synchronization of movements is found to play an essential role in the interactive behavior of humans. Due to its ubiquity in human life, interpersonal synchronization is experimentally investigated in various tasks that require jointly performed movements in a shared workspace: When walking in a group, humans tend to synchronize their gait [1]. Two people sitting next to each other in rocking chairs are found to synchronize their rocking movements [2], even if the natural frequencies of the chairs differ. Similar behavior is observed in laboratory tasks such as pendulum swinging [3] or pure leg movements [4]. Even during goal-directed tapping that requires precise arm movements [5], synchronization among human dyads is emerging naturally without being instructed or demanded for the task. In this task, interpersonal movement synchronization can be clearly quantified as a coupled dynamical process [6]. Studies on the social aspects of synchronization highlight that falling into synchrony with partners enhances perceptual sensitivity toward each other, fosters cooperative abilities [7] and leads to the attribution of more positive characteristics to the interaction partner [8]. These works give rise to the hypothesis, that bidirectional motor coordination with synchronization as its key concept is a promising way to increase the social competence of robots when interacting with humans [9].

Inspired by the appealing prospect to enrich the interaction repertoire of robots, this article addresses the challenge of designing interactive behavior for artificial agents engaging in repetitive *joint action tasks*. These tasks involve actions performed by two or more individuals in a common social setting, inducing action coordination in space and time [10]. Based on synchronization theory of coupled dynamical systems [11], we present a synchronization concept for repetitive, goal-directed movements composed by mixed continuous and discrete primitives.

Movement Synchronization among Humans and Machines

One line of research on human synchronization behavior follows the dynamical systems approach. Patterns of coordination are considered to result from attractors of dynamical systems, that model interconnected perception-action loops [12]. This concept is also called behavioral dynamics [13]. Investigating intrapersonal limb coordination, Haken et al. [14] propose a minimal dynamical model of coupled oscillators, which is known as the Haken-Kelso-Bunz (HKB) model. It reproduces the main coordination features

observed during rhythmic bi-manual finger-tapping. The HKB model family qualitatively explains interpersonal movement synchronization in rhythmic paradigms as well [2,15]. In this vein, the rigorous design of rhythmic movement behavior by dynamical systems in the state space is performed by Jirsa and Kelso [16], which the authors call the excitator model. Common to these approaches is the monolithic encoding of movement coordination and reproduction, making them rather task specific. A second line of research on human synchronization behavior is devoted to the intended synchronization of human rhythmic movements with respect to purely discrete, periodic stimuli such as auditory metronome beats, which is often called sensorimotor synchronization (SMS). Linear models of asynchrony correction based on the Wing-Kristofferson model [17] explain perceptual and motor variabilities from an information-processing point of view, see [18,19] for an exhaustive review. It is recently debated whether hybrid incarnations of both the dynamical systems approach and the linear error correction concept may exist [20] or not [21], or whether these model classes simply account for different synchronization processes present in the task [22]. Irrespective of the underlying process, it is found that discrete perceptual information such as distinguishable events during continuous movements provides anchoring points for time keeping with a stimulus and, thus, fosters human SMS [23]. Notably, humans are found to rapidly adjust their pacing toward each other during dyadic finger tapping, thus improving coordination by mutually coupled SMS [24].

Limit cycle systems creating rhythmic movement based on self-sustained oscillators are also called central pattern generators (CPGs) in robotics. Entrainment tasks, such as robot drumming [25], are modeled by CPGs, where phase locking regarding the beats is achieved. An extension of the CPG approach by reconfigurable dynamical systems is proposed by Degallier et al. [26] to generate mixed discrete and rhythmic movements in multiple degrees of freedom. The encoding of periodic movements based on adaptive frequency oscillators is realized in Gams et al. [27] and developed further by Petric et al. [28]. Frequency and phase tuning shows a rather slow rate of convergence for non-stationary trajectories. Though CPGs model robust and flexible motor behavior, an open issue is the missing methodology to systematically design and specify CPGs in a task-oriented way. For profound reviews on the design and application of CPGs, the reader is referred to [29,30]. Some works investigate human-machine rhythmic coordination. Mutual entrainment of movements is achieved by rendering visual or acoustic stimuli to the human as real-time feedback. The concept of virtual partner interaction (VPI) is introduced in [31]. In a proof-of-concept implementation, the coordination of finger movements between a human and a visually-rendered, virtual agent driven by the HKB model is explored systematically. In various applications, rhythmic entrainment between humans and robots is investigated. Popular examples are human-robot rope turning [32,33] or the imitation of human rhythmic movements of selected target frequencies [34] by means of phase-locked loops (PLL) [35]. Both human-robot handshaking [36] and physical assistance for rhythmic knee movements [37] are realized based on the Matsuoka neural oscillator [38]. Here, Sato et al. [39] achieve encoding of rhythmic movements and implicit synchronization through an on-line polynomial design of the attractor dynamics, which is originally proposed by Okada et al. [40].

However, the above works focus either on fundamental research of human synchronization behavior or, within human-machine interaction, on applications in purely rhythmic tasks. To the authors' best knowledge, none of the existing works, except our previous [5,6], analyzes and models synchronization of hybrid action tasks composed by mixed continuous and discrete primitives with application to human-robot dyads.

Contribution

In this article, we develop a concept of movement synchronization for repetitive joint action tasks. Those tasks are assumed to be described by closed movement trajectories that can be goal-directed and comprise multiple primitives. The modeling concept pursued in our analytical work on human synchronization behavior [6] is generalized to enable the design of synchronization behavior for robotic agents in a wide range of tasks: Based on oscillator theory, limit cycle representations of the trajectories in state space are used to derive the phase variable, even for sequences of multiple primitives. Relevant synchronization modes within pairs of limit cycles are synthesized considering both continuous phases and discrete events from a unifying point of view. In line with the behavioral dynamics perspective [13,41], we design a dynamical process to synchronize the derived modes. Movement generation is addressed as well, in order to enable a robotic agent that is equipped with synchronization behavior engage in repetitive joint action tasks. The presented experimental study employing a full-sized, anthropomorphic robot serves not only as proof of concept; it also defines a versatile testbed for the investigation of human-robot interactive behavior in realistic settings.

The remainder of this article is organized as follows. First, we clarify the required assumptions and definitions. Based on those, synchronization modes are analyzed and dynamical synchronization behavior is designed accordingly. Next, the required transformations between phase variables and movement trajectories are developed. After the design concept, we describe the human-robot experiment, its implementation and the applied measures. A detailed assessment and evaluation of the implemented synchronization behavior is presented. After a discussion of the results and insights, we sum up and draw the conclusions.

Bold characters are used for denoting vectors in this article. Superscripts ^{a} and ^{b} are used when variables belonging to agent 'a' and agent 'b' need to be distinguished. For clarity these superscripts are omitted otherwise.

Problem Setting and Definitions

This section provides the reader with the formal representations and definitions that are used in this article to characterize the joint action task as well as movement synchronization.

Representation of Repetitive Joint Action Tasks

The notion of joint action [10], originated from cognitive psychology, is adopted in this work, whereas we extend joint action to robotic agents as well. Let each agent's part of the joint action task, which we call the individual task, be represented by a state trajectory $\boldsymbol{\xi}(t)$, i.e. the evolution of the vector of relevant states $\boldsymbol{\xi}\in\mathbb{R}^n$ over time t. The state vector can be composed by the configuration of the agent's limbs, their hand (effector) position, or any other coordinates that describe the movements associated with the individual task.

Note. A certain set of states is considered suitable if the information conveyed through the chosen description allows to explain and model the synchronization behavior of the agents.

Limit cycle trajectory. The concept of movement synchronization exploits the repetitive aspect of the individual task. Therefore, the state trajectory is required to be *cyclic*, i.e. for any time t and finite time spans T the condition

$$\boldsymbol{\xi}(t+T)=\boldsymbol{\xi}(t) \tag{1}$$

holds. The smallest $T>0$ which fulfills (1) is denoted the *period*. It follows that the state space representation of $\boldsymbol{\xi}(t)$ is of circular shape, which is denoted the *limit cycle* γ, see Fig. 1. Due to interaction between the agents, the period T is time-varying and consequently, γ is strictly speaking not periodic.

Note. For trajectories obtained from noisy measurements, condition (1) is relaxed by examining the return times to the Poincaré secant surface [42], allowing for $\boldsymbol{\xi}(t+T)\approx\boldsymbol{\xi}(t)$.

Primitives, events and durations. The limit cycle γ is assumed to be composed by a number of L segments $\mu_l\subseteq\gamma$ in an ordered sequence $l=1,...,L$. These are called *primitives*. Each primitive μ_l is delimited by two segmentation points, the start point $\boldsymbol{\xi}_{l-1}=\boldsymbol{\xi}(t_{l-1,i})$ and the end point $\boldsymbol{\xi}_l=\boldsymbol{\xi}(t_{l,i})$, as illustrated in Fig. 2(a). The positive index $i\in\mathbb{N}$ denotes the ith period. The period is taken by $T_i=t_{L,i}-t_{0,i}$ in the following. It has to be noted that $\boldsymbol{\xi}_L\equiv\boldsymbol{\xi}_0$ and $t_{L,i}=t_{0,i+1}$ respectively, since $\boldsymbol{\xi}(t)$ is cyclic. The times $t_{l-1,i}$ and $t_{l,i}$ are called *events*, see Fig. 2(b). Without loss of generality, we choose segmentation points featuring discriminable events, such as local extrema of the movement with vanishing velocity [43]. Segmentation points with zero or negligible velocity persisting for non-zero time intervals are considered as postures [44] and separate dwell primitives respectively. Those dwell primitives are also delimited by event pairs, denoting the times of movement stop and start. Discriminable events in cyclic trajectories are shown to support human mechanisms of temporal error correction [23], and thus affect human synchronization behavior.

Note. The segmentation points are assumed to be such that any task-related constraints on the state can be satisfied, e.g. goal points or forbidden state regions.

The times $t_{l-1,i}$ and $t_{l,i}$ define the *primitive duration*

$$T_{l,i}=t_{l,i}-t_{l-1,i}. \tag{2}$$

Relating the *current* primitive duration $T_l=T_{l,i}$ and the *current* period $T=T_i$ with index i such that $t_{0,i}<t\le t_{L,i}$, we further define the *relative primitive duration*

$$d_l=\frac{T_l}{T},\quad \text{with}\quad \sum_{l=1}^{L} d_l=1. \tag{3}$$

The distribution $\boldsymbol{d}=[d_1\ ...\ d_L]^{\mathrm{T}}$ gathering d_l in a vector scales the primitive durations T_l under modulations of T.

Synchronization of Limit Cycle Pairs

The limit cycle γ is assumed to be originated from a self-sustained oscillation, which allows us to apply the theory of limit cycle oscillators. The notion of phase is introduced to describe the motion of the state on the limit cycle. The definition of synchronization relates both the phase and events of a pair of limit cycles to each other and therefore, characterizes coordination in time.

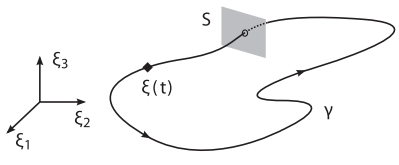

Figure 1. Limit cycle γ of an exemplary cyclic state trajectory $\xi(t)$ in its state space with $\xi\in\mathbb{R}^3$. If γ is cyclic, yet not closed exactly, the period T is determined by the return time of ξ to the Poincaré secant surface S.
doi:10.1371/journal.pone.0095195.g001

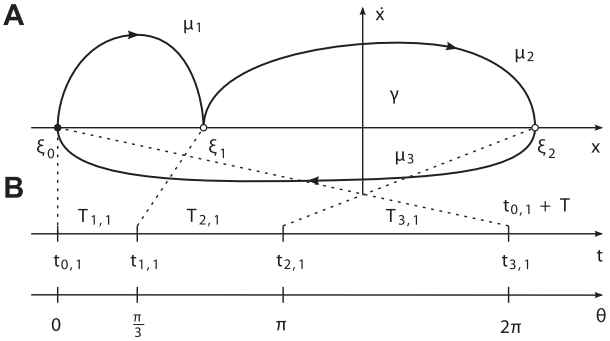

Figure 2. Characterization of the limit cycle. (A) Exemplary limit cycle γ with the state $\boldsymbol{\xi}=[x\ \dot{x}]^{\mathrm{T}}$ and $L=3$ primitives. The segmentation points $\boldsymbol{\xi}_i$ are given by the intersection of γ with the abscissa. (B) The corresponding events $t_{l,1}$, primitive durations $T_{l,1}$ and the uniformly growing phase θ depicted for $i=1$.
doi:10.1371/journal.pone.0095195.g002

The phase variable. Through a coordinate transformation, the limit cycle is re-parameterized by the one-dimensional variable θ that is called the *phase* and describes the motion on γ and the $(n-1)$-dimensional vector of *amplitudes* that describe motions transverse to γ. This transformation is not unique, and thus, different decompositions can be found for a certain limit cycle [45]. In our setting of goal-directed tasks, we assume the amplitudes to be constrained by the segmentation points delimiting the primitives, compactly gathered in $\Xi=[\boldsymbol{\xi}_1\ ...\ \boldsymbol{\xi}_L]$. Consequently, only the phase is considered to be governed by synchronization in the following.

Among all possible transformations, we choose the phase obtained from the harmonic phase oscillator, which is one of the simplest oscillator models. Its unperturbed oscillations evolve at constant phase velocity $\dot{\theta}=\omega$, with ω denoting the natural frequency. Accordingly, its phase trajectory is defined

$$\theta(t)=\omega t+\theta_0, \tag{4}$$

which is growing uniformly in time. By setting $\omega=\frac{2\pi}{T}$, we further define the phase to be angular and 2π-periodic, evaluating

$$\theta(iT)=2\pi i+\theta_0, \tag{5}$$

with any initial phase θ_0. Finally, the phase $\theta(t)$ needs to be uniquely related to the state $\boldsymbol{\xi}(t)$. We deliberately choose θ_0 such that $\theta(t_{0,1})=0$ is anchored to the point $\boldsymbol{\xi}(t_{0,1})=\boldsymbol{\xi}_0$ marking the event $t_{0,1}$, cf. Fig. 2(b). The phase of a stationary limit cycle with constant period T is readily given by (4), which is analogous to the marker technique in [42]. The important case of a non-stationary limit-cycle with a-priori unknown period $T(t)$ is addressed later.

Note. The above transformation can be understood as a decomposition of the task into the phase, which is the *voluntary* degree of freedom available for synchronization, and the amplitudes, which are the remaining degrees of freedom *necessarily* complying with the task goals.

Phase and event synchronization. With the above definition of phase and under the assumption that the phase is originated from a self-sustained oscillating entity, a synchronization problem between a pair of phase oscillators is posed accounting for a dyad's coordination in time. The oscillators are assumed to be mutually coupled through some coupling function and completely described by their phases $\theta^{a/b}(t)$ defined on the limit cycles $\gamma^{a/b}$. If the phase difference

$$\Phi(t)=\theta^{a}(t)-\theta^{b}(t) \tag{6}$$

is bounded by a positive constant $\epsilon\in\mathbb{R}$

$$|\Phi(t)|<\epsilon \quad \forall t, \tag{7}$$

the limit cycles show *phase synchronization* [11] of order 1:1. Higher order synchronization is not addressed in this article for the sake of simplicity.

In addition, the quasi-simultaneous appearance of event pairs is considered, known as event synchronization [46]. Let $t_{l,i}$ denote the time of the lth event in the ith period of γ. We define, that the event pair denoted by the tuple $(t^{a}_{l^a},t^{b}_{l^b})$ shows *event synchronization*, if the events keep the temporal relation

$$\left|t^{a}_{l^a,i^a}-t^{b}_{l^b,i^a+m}\right|<\Delta t \quad \forall i^a, \tag{8}$$

with some time span Δt. Choosing $m=const.$, with $m\in\mathbb{N}$ ensures to test for event synchronization of order 1:1. The choice of Δt is considered as problem dependent. To avoid ambiguities, a reasonable upper bound is given by

$$\Delta t\leq\frac{1}{2}\min_{i^a,i^b}\{T^{a}_{l^a,i^a},T^{a}_{l^a+1,i^a},T^{b}_{l^b,i^b},T^{b}_{l^b+1,i^b}\}, \tag{9}$$

which is half the minimum primitive duration or half the minimum inter-event distance in the neighborhood of the considered pair $\left(t^{a}_{l^a},t^{b}_{l^b}\right)$.

Note. The above notion of event synchronization implies phase synchronization, since the time lag and thus, the phase difference between the considered events is bounded. Event synchronization depending on the definition of relevant events provides a problem-specific characterization of the temporal organization of two limit cycles.

Design of Synchronization Behavior

Following the above definitions of phase and event synchronization and inspired by principles of human movement synchronization, in this Section we design synchronization behavior with application to repetitive joint action tasks. Accounting for the derived descriptions of possible synchronization modes, a unified synchronization process is developed.

Synchronization Modes

After analyzing the common modes of the synchronization between quasi-harmonic trajectories, which usually result from rhythmic movement tasks, we broaden the repertoire of potential synchronization modes between limit cycles featuring multiple primitives and events.

Modes between harmonic limit cycles. Research on movement synchronization within human dyads has mainly focused on task paradigms requiring purely rhythmic movements such as finger tapping, leg or pendulum swinging. These tasks are usually described by one-dimensional motion trajectories, e.g. with the state $\boldsymbol{\xi}\in\mathbb{R}^2$ embedded in a position-velocity state space. Typically, each period of the trajectory is composed by two nearly equal and sinusoidal half-periods, allowing to treat the oscillation as harmonic. Following the definitions made above, the limit cycle γ of the state trajectory $\boldsymbol{\xi}(t)$ is segmented into $L=2$ primitives $\mu_l\subset\gamma$, $l=1,2$, which are symmetric due to their relative primitive durations with $d_l=\frac{1}{2}$ being constant and equal, cf. Fig. 3. For pairs of limit cycles $\gamma^{a/b}$ originated from harmonic oscillations, the notions of the *in-phase* and the *anti-phase* relation usually characterize the common modes of synchronization. When we calculate the relative phase difference

$$\Phi_r(t)=\Phi(t) \bmod 2\pi, \tag{10}$$

with $\Phi(t)$ from (6) and mod denoting the mathematical modulo division, the in-phase and the anti-phase mode map to $\Phi_r=0$ and $\Phi_r=\pi$ respectively, cf. Fig. 3(b).

These modes are equivalently described by event synchronization according to the above definition of synchronization. Evaluating the phase (4) at the event $t_{l,i}$ yields with (3)

$$\theta(t_{l,i})=2\pi\sum_{j=1}^{l}d_j+2\pi(i-1). \tag{11}$$

Thus, we obtain $\theta(t_{1,i}) \bmod 2\pi=\pi$ and $\theta(t_{2,i}) \bmod 2\pi=0$ for symmetric primitives with $d^{a/b}_1=d^{a/b}_2=\frac{1}{2}$. It follows that the relative phase difference (10) evaluates $\Phi_{r,e}=0$ and $\Phi_{r,e}=\pi$, if the event pairs $(t^{a}_{1/2},t^{b}_{1/2})$ and $(t^{a}_{1/2},t^{b}_{2/1})$ appear synchronized. Summing up, quasi-harmonic cycles are considered to be composed by two symmetric primitives and events respectively. Their common synchronization modes are sufficiently described by the phase dynamics of coupled oscillator models, e.g. [6,14,47,48].

Modes between multiple-primitive limit cycles. In repetitive joint action tasks, the limit cycles $\gamma^{a/b}$ represent the agents' individual tasks. Those can be composed by different sequences of multiple primitives, i.e. with the number of primitives $L^{a/b}>2$, the distributions of relative primitive durations $\boldsymbol{d}^{a}\neq\boldsymbol{d}^{b}$, or both. Here, the relevant modes of synchronization are assumed to describe the (simultaneous) synchronization of one or more event pairs $(t^{a}_{l^a},t^{b}_{l^b})$, see the modes in Fig. 4(c)–(d).

The example in Fig. 4 illustrates, that phase synchronization is not sufficient to describe all of these modes. Phase synchronization models stable equilibrium points $\Phi_{r,e}$ of the phase difference which lead to $\Phi_r(t)\rightarrow\Phi_{r,e}$ and imply $T^{a}-T^{b}\rightarrow 0$ in the domains of attraction. This allows to synchronize single event pairs, like the one depicted in Fig. 4(c). If the within-cycle distributions of events differ $\boldsymbol{d}^{a}\neq\boldsymbol{d}^{b}$ like in our example, the simultaneous synchronization of not more than one event pair is explained by the phase dynamics, since the events scale under changes of $T^{a/b}$ with the distributions $\boldsymbol{d}^{a/b}$, which are, however, left uncontrolled. Obviously, the simultaneous synchronization of *multiple* event pairs requires an additional adjustment of $\boldsymbol{d}^{a/b}$, see Fig. 4(d).

Note. Only a task-dependent subset of events might be synchronized, e.g. only those that are perceived by the interaction partner.

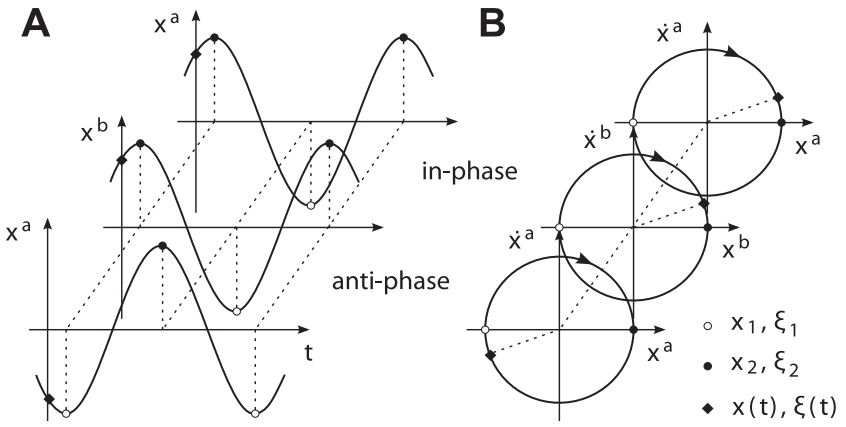

Figure 3. Modes between harmonic oscillations. Phase synchronization resulting in in-phase or anti-phase relations comes about with event synchronization with respect to the segmentation points $\xi_1^{a/b}$ and $\xi_2^{a/b}$. (A) Motion trajectories $x^{a/b}(t)$ describing the temporal relation. (B) Their limit cycle representations $\gamma^{a/b}$ in a position-velocity state space, illustrating the phase difference.
doi:10.1371/journal.pone.0095195.g003

Dynamical Synchronization Process

Synchronization behavior is modeled in line with the *dynamical systems approach* [13], which explains stable behavioral patterns by attractors of dynamical systems. First, we review the phase dynamics modeling the synchronization of human dyads performing quasi-harmonic limit cycles in a goal-directed movement task. The above analysis shows, that phase synchronization is able to account only for a limited number of possible synchronization modes. Therefore, we design a unified synchronization process that features the simultaneous synchronization of multiple event pairs.

Model of coupled phase oscillators. In accordance to the definition of phase synchronization, the model structure is given by a pair of cross-coupled phase oscillators

$$\dot{\theta}^{a} = \omega^{a} + G^{a}(\theta^{b} - \theta^{a}) \tag{12}$$

$$\dot{\theta}^{b} = \omega^{b} + G^{b}(\theta^{a} - \theta^{b}), \tag{13}$$

with the natural frequencies $\omega^{a/b}$, and the coupling functions $G^{a/b}$ depending on the phase difference between the oscillators. By subtracting (13) from (12), we obtain the phase difference dynamics

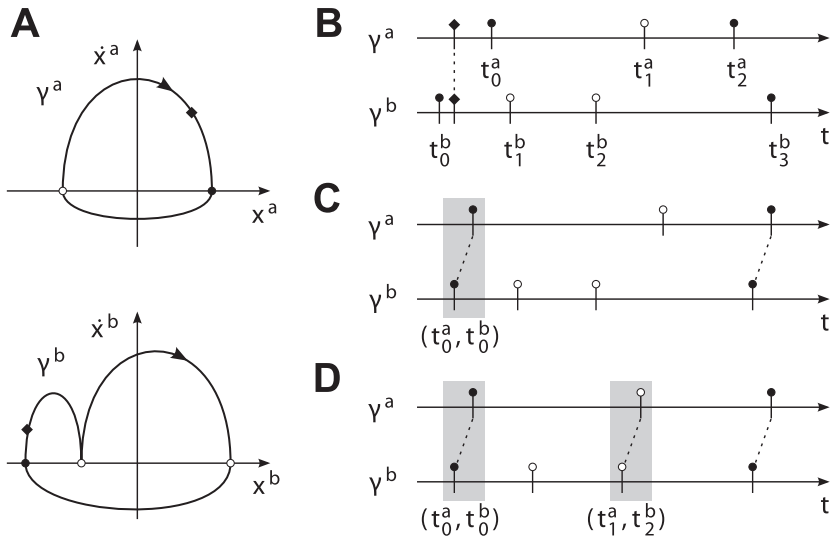

Figure 4. Event synchronization of heterogeneous limit cycle pairs. (A) Exemplary limit cycles $\gamma^{a/b}$ with $L^{a}=2$ and $L^{b}=3$ primitives in position-velocity state spaces. The evolution of the events in $\gamma^{a/b}$, (B) without synchronization, (C) with synchronization of the event pair (t_0^a,t_0^b) as achieved by phase synchronization, (D) with additional synchronization of (t_1^a,t_2^b). The shaded areas denote the time span Δt defining event synchronization.
doi:10.1371/journal.pone.0095195.g004

$$\dot{\Phi} = \Delta\omega + H(\Phi), \tag{14}$$

with $\dot{\Phi} = \dot{\theta}^{a} - \dot{\theta}^{b}$ and the frequency detuning

$$\Delta\omega = \omega^{a} - \omega^{b}. \tag{15}$$

The function H is the vector field of Φ forming the attractor landscape, and thus, the preferred modes of phase synchronization.

Note. Synchronization behavior is assumed to be voluntary and compliant with the task-related goals. We therefore require the coupling functions to be weak and 2π-periodic, i.e. equilibrium points Φ_e are equivalently described by equilibrium points $\Phi_{r,e}$ of the relative phase difference (10) between the oscillators. Consequently, a large enough frequency detuning $\Delta\omega$ completely eliminates stable attractors, which is found to be in line with unintentional coordination behavior of humans [49].

In the following, we review a realization of the coupling functions $G^{a/b}$ that accounts for the observed process of inter-human movement synchronization [6]. The proposed model structure is based on the classical *Kuramoto model* [50]. Its equations of motion read

$$\dot{\theta}^{a} = \omega^{a} + K\sin\left[2\left(\theta^{b} - \theta^{a}\right)\right] \tag{16}$$

$$\dot{\theta}^{b} = \omega^{b} + K\sin\left[2\left(\theta^{a} - \theta^{b}\right)\right], \tag{17}$$

which we call the *extended Kuramoto model*. The natural frequencies model the individually preferred speed of task performance, whereas the sinusoidal coupling with the isotropic gain K replicates the dyad's interactive behavior. We obtain the phase difference dynamics

$$\dot{\Phi} = \Delta\omega - 2K\sin(2\Phi), \tag{18}$$

featuring two point attractors around $\Phi_{r,e,1} = 0$ and $\Phi_{r,e,2} = \pi$, see Fig. 5(a) for a visualization of the vector field. The dynamics (18) replicate the synchronization process of human dyads that leads to in-phase and anti-phase modes between quasi-harmonic, yet goal-directed movements [5]. Details concerning this model, e.g. its stability properties can be found in [6].

Note. The extended Kuramoto model implies equal attractor strengths, as both attractors were met nearly equally often in the experimental task.

Synchronization of single event pairs. In-phase and anti-phase synchronization between harmonic limit cycles is now generalized to synchronization modes of single event pairs in arbitrary combinations. Again, stable modes of synchronization are mapped to stable equilibrium points $\Phi_{r,e}$ of the vector field H. The values of $\Phi_{r,e}$, i.e. the locations in the attractor landscape, depend on the definition of the events $t_0^{a/b}$ for which the initial phases (4) evaluate $\theta_0^{a/b} = 0$. It makes sense to define them such that the pair (t_0^{a}, t_0^{b}) denotes a synchronization mode, with the corresponding attractor $\Phi_{r,e} = 0$. Using (11), the synchronization mode of any event pair $(t_{j^a}^{a}, t_{j^b}^{b})$ is then expressed by the equilibrium phase difference

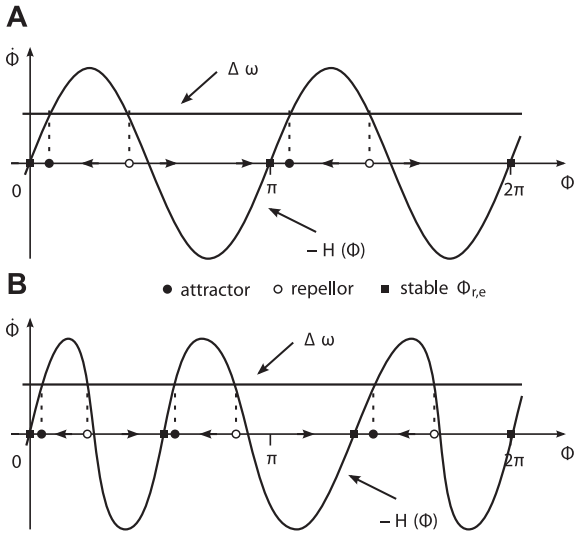

Figure 5. R.h.s. terms of the phase difference dynamics (14) over $\Phi \in [0, 2\pi]$. The intersection points of the graphs of $\Delta\omega$ and $-H(\Phi)$ denote equilibria with $\dot{\Phi} = 0$. The vector fields are illustrated on the abscissae. (A) The extended Kuramoto model featuring two equally-spaced attractors. (B) Exemplary phase dynamics featuring three attractors determined via (19).
doi:10.1371/journal.pone.0095195.g005

$$\Phi_{e} = \theta^{a}(t_{j^a}^{a}) - \theta^{b}(t_{j^b}^{b}) = 2\pi\left(\sum_{j=1}^{j^a} d_j^{a} - \sum_{j=1}^{j^b} d_j^{b}\right). \tag{19}$$

For each event pair representing a synchronized mode, the vector field H of the phase difference dynamics (14) needs to feature a point attractor $\Phi_{r,e}$, which is obtained from (19) with (10), see Fig. 5(b) for an example. The following points summarize the properties common to the design of the vector field H:

- The phase plot is of oscillating shape, modeling an alternating sequence of attractors and repellors.
- The gradient and extrema in the vicinity of an equilibrium point $\Phi_{r,e}$ define its strength and region of attraction respectively [6], given a certain frequency detuning $\Delta\omega$.
- In order to obtain relative synchronization, we require $H(\Phi) = H(\Phi + 2\pi)$.
- In contrast to the extended Kuramoto model and similar coordination models, symmetry $H(-\Phi) = -H(\Phi)$ is generally not fulfilled.
- Positive (negative) values $\Delta\omega$ yield positive (negative) shifts of the attractor points.

Note. The attractor landscape of the phase dynamics becomes time-varying, if the relative primitive durations $\boldsymbol{d}^{a/b}$ are subject to adjustment.

Synchronization of multiple events pairs. The coupled process (12), (13) accounts for synchronization modes that can be achieved by mutual entrainment of both periods and phase difference within certain domains of attraction. However, the simultaneous synchronization of multiple event pairs remains generally unexplained, as pointed out in the previous section. Therefore, the relative primitive durations $\boldsymbol{d}^{a/b}$ are proposed as

additional degrees of freedom, governed by a cross-coupled dynamical process of the form

$$\dot{\boldsymbol{d}}^{\mathrm{a}} = \boldsymbol{D}^{\mathrm{a}}(\boldsymbol{d}^{\mathrm{a}},\boldsymbol{d}^{\mathrm{b}}), \tag{20}$$

$$\dot{\boldsymbol{d}}^{\mathrm{b}} = \boldsymbol{D}^{\mathrm{b}}(\boldsymbol{d}^{\mathrm{b}},\boldsymbol{d}^{\mathrm{a}}), \tag{21}$$

with $\boldsymbol{d}^{\mathrm{a/b}}$ subject to normalization $\sum_{l=1}^{L^{\mathrm{a/b}}} d_l^{\mathrm{a/b}} = 1$. In Fig. 6, the degrees of freedom of the overall synchronization process are illustrated for the above mode with respect to two event pairs. Synchronization modes that would require to accommodate large differences between components of $\boldsymbol{d}^{\mathrm{a/b}}$ or between combinations thereof might be infeasible, e.g. due to velocity constraints related to the agents or their individual tasks. The process (20), (21) is therefore assumed to be subject to locally bounded regions of attraction. Such boundedness is similar to the range of frequency detuning $\Delta\omega$ in (14), which limits stable phase synchronization.

Note. Normalization is preserved e.g. by adjusting the components of $\boldsymbol{d}^{\mathrm{a/b}}$ such that $\sum_{l=1}^{L^{\mathrm{a/b}}} \dot{d}_l^{\mathrm{a/b}} = 0$ holds, which is the derivative of the normalization constraint.

In the following, we outline a possible realization of the process (20), (21) featuring the mode illustrated in Fig. 6(b). In this mode, the event pairs $(t_0^{\mathrm{a}},t_0^{\mathrm{b}})$ and $(t_1^{\mathrm{a}},t_2^{\mathrm{b}})$ appear synchronized simultaneously. The former is readily synchronized by the phase dynamics (12), (13) employing the stable equilibrium point $\Phi_{\mathrm{r,e}} = 0$. In order to additionally synchronize the latter, we design the entrainment of $\boldsymbol{d}^{\mathrm{a}}$ according to

$$\dot{d}_1^{\mathrm{a}} = -\dot{d}_2^{\mathrm{a}}, \tag{22}$$

$$\dot{d}_2^{\mathrm{a}} = K_{\mathrm{d}} \sin \frac{\pi\left(d_{3,\mathrm{s}}^{\mathrm{b}} - d_2^{\mathrm{a}}\right)}{d_{2,\mathrm{h}}^{a} - d_{2,\mathrm{l}}^{a}}. \tag{23}$$

By (22), normalization is preserved. The gain $K_d > 0$ in (23) enforces the solution $d_2^{\mathrm{a}} = d_{3,\mathrm{s}}^{\mathrm{b}}$ to be stable, saturated by

$$d_{3,\mathrm{s}}^{\mathrm{b}} = \begin{cases} d_{2,\mathrm{l}}^{a}, & \text{if } d_3^{\mathrm{b}} < d_{2,\mathrm{l}}^{a} \\ d_3^{\mathrm{b}}, & \text{if } d_{2,\mathrm{l}}^{a} \le d_3^{\mathrm{b}} \le d_{2,\mathrm{h}}^{a} \\ d_{2,\mathrm{h}}^{a}, & \text{otherwise.} \end{cases}$$

The thresholds $d_{2,\mathrm{l}}^{a}$ and $d_{2,\mathrm{h}}^{a}$ define the lower and upper bound on the entrainment of d_2^{a}. Assuming isotropic coupling between the agents, the entrainment of $\boldsymbol{d}^{\mathrm{b}}$ is designed analogously.

Transformation between Movement and Phase

The synchronization process developed in the previous section governs the phase variables $\theta^{\mathrm{a/b}}(t)$ as well as the relative primitive durations $\boldsymbol{d}^{\mathrm{a/b}}(t)$. Since we target the integration of the synchronization behavior in the perception-action loop of robotic agents, the movement trajectories need to be transformed on-line into the process variables and vice versa.

From Movement to Phase

The problem considered first is how to determine the partner's phase *instantaneously*, based on measurements of the movement trajectory. Besides the instantaneous phase $\hat{\theta}(t)$, the solution presented in the following also provides event predictions $\hat{t}_{l,i}$, and thus via (2) and (3), predictions of the relative primitive durations $\hat{\boldsymbol{d}}(t)$.

Existing methods and open issues. Different methods have been applied to extract instantaneous phase variables from limit cycles that are known only by their observables, e.g. their cyclic movement trajectories. However, none of them fulfills our requirements entirely. First and foremost, only one-dimensional and narrow-band trajectories can be analyzed properly by the common methods. These methods are the analytic signal concept based on the Hilbert transform [42] and the state space methods [51] retrieving the trigonometrical phase angle in a position-velocity state space. Moreover, the former is restricted to off-line analysis, see [6] and [52] for a comparative discussion. The technique of linear phase interpolation between single marker events per period [42] can be considered analogous to the analysis of return times on the Poincaré map. Since this technique is

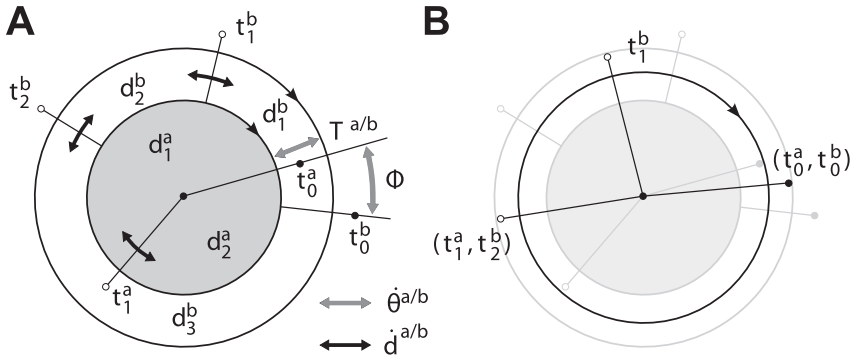

Figure 6. Circular illustration of the synchronization problem between two limit cycles. The exemplary limit cycles γ^{a} (inner circle) and γ^{b} (outer circle) are introduced in Fig. 4. (A) The degrees of freedom available for synchronization: The periods $T^{\mathrm{a/b}}$ and the phase difference Φ are both governed by the process (12), (13). The relative primitive durations $\boldsymbol{d}^{\mathrm{a/b}}$ are governed by the process (20), (21). (B) Perfect synchronization of the event pairs $(t_0^{\mathrm{a}},t_0^{\mathrm{b}})$ and $(t_1^{\mathrm{a}},t_2^{\mathrm{b}})$, leading to coincident circles and events.
doi:10.1371/journal.pone.0095195.g006

applicable regardless of the frequency components and the dimensionality of the analyzed trajectory, we adopted our phase definition accordingly. However, the following challenges remain, preventing to calculate the phase straightforward via (4):

- Movement variabilities due to interaction or other perturbations considered as noise will cause the limit cycles of human partners to be *non-stationary*, i.e. the period $T(t)$ and thus, also the relative primitive durations $\boldsymbol{d}(t)$ become instantaneous variables.
- The variables $T(t)$ and $\boldsymbol{d}(t)$ refer to a parameterization of the current period as a whole. Hence, on-line applications require estimates that are continuously predicting the future values these parameters take at period completion.

The instantaneous phase of non-stationary limit cycles. The desired phase variable is required to instantaneously reflect changes of the period, while it is also required to comply with the definition (4) prescribing the unperturbed phase evolution. Given a *prediction* of the event $\hat{t}_{L,i}(t)$ denoting the time of completion of the current period i, we propose a phase estimate for the time $t_{0,i} \le t < \hat{t}_{L,i}(t)$ given by the solution of

$$\hat{\omega}(t) = \dot{\hat{\theta}} = \frac{2\pi i - \hat{\theta}}{\hat{t}_{L,i}(t) - t}, \tag{24}$$

which is a linear differential equation with time-varying coefficients. The initial condition reads $\hat{\theta}(t_{0,i}) = 2\pi(i-1)$. Time-varying predictions of the event $\hat{t}_{L,i}(t)$ are instantaneously reflected by the phase velocity (24), see example plot in Fig. 7. Numerical integration of (24) yields the phase trajectory

$$\hat{\theta}(t) = \int_{t_{0,i}}^{t} \hat{\omega}(\tau)\mathrm{d}\tau + \hat{\theta}(t_{0,i}), \tag{25}$$

which is due to $\hat{\omega}(t) \ge 0$ monotonically growing. For times $t \to \hat{t}_{L,i}(t)$, the solution of (24) converges to $\hat{\theta} = 2\pi i$.

Note. Given a stationary limit cycle and assuming perfect prediction $\hat{t}_{L,i} = t_{L,i} = const.$, the solution of (24) can be derived analytically. It reads

$$\hat{\theta}(t) = \frac{2\pi}{\hat{t}_{L,i} - t_{0,i}}(t - t_{0,i}) + \hat{\theta}(t_{0,i}), \tag{26}$$

which is obviously the harmonic angular phase complying with definition (4), cf. gray graphs in Fig. 7.

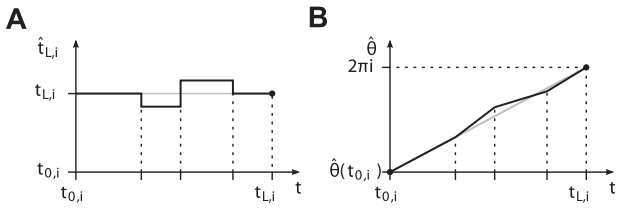

Figure 7. Instantaneous phase calculation. (A) Exemplary evolution of the predicted event $\hat{t}_{L,i}$ over time t. (B) Corresponding evolution of the phase $\hat{\theta}$ obtained from (25). The slope of $\hat{\theta}$ instantaneously relates the left over phase $2\pi i - \hat{\theta} \ge 0$ in period i to the left over time span $\hat{t}_{L,i} - t > 0$. Black dots denote boundary conditions. Gray graphs depict perfect prediction and the harmonic phase respectively.
doi:10.1371/journal.pone.0095195.g007

Prediction of events from observation. Both the instantaneous phase (25) denoting the numerical solution of (24) and the relative primitive durations obtained from (2) and (3) require on-line predictions of the events $\hat{t}_{l,i}$, $l = 1,...,L$ in the current period i. To that extent, we assume the state $\boldsymbol{\xi}$ to be fully observable up to time t. The task-related segmentation points $\Xi = [\boldsymbol{\xi}_1 \ ... \ \boldsymbol{\xi}_L]$ are assumed to be known and constant.

We propose the following two-step technique to obtain predictions from experimental measurements:

- *Acquiring limit cycles:* Reference limit cycles

$$\gamma^r : \boldsymbol{\xi}^r(t^r), \text{ with } t^r \in [t_0^r, t_L^r] \tag{27}$$

  are acquired over single, complete periods. A family of limit cycles γ^r, $r = 1,...,R$ is built from a number of R cycles. These feature differing periods T^r covering the expected range of periods, see example in Fig. 8(a).
- *Classifying limit cycles and predicting events:* The current state $\boldsymbol{\xi}$ is classified with respect to the family of reference limit cycles. First, the similarity to each γ^r is determined by the respective minimum of the distance metric

$$\Delta\xi^r = \min_{\xi^r \in \gamma^r} \sqrt{(\boldsymbol{\xi}^r - \boldsymbol{\xi})^{\mathrm{T}} Q (\boldsymbol{\xi}^r - \boldsymbol{\xi})}, \tag{28}$$

  with Q being a $n \times n$ positive definite weighing matrix. Next, the closest cycle γ^{r^*} is selected by

$$r^* = \arg\min_r \Delta\xi^r. \tag{29}$$

If the state $\boldsymbol{\xi}$ is close to the segmentation points, the distances $\Delta\xi^r$ are nearly equal. In this case, undesired switchings of r^* are avoided by switching from previous $r^{*\prime}$ to current r^* only if a certain threshold

$$\Delta\xi_{\mathrm{th}} < \Delta\xi^{r^{*\prime}}(t) - \Delta\xi^{r^*}(t)$$

is exceeded. Finally, predictions of any future event $\hat{t}_{l,i}$ at time t are obtained from

$$\hat{t}_{l,i} = t + t_l^{r^*} - t^{r^*}, \text{ with } t_l^{r^*} > t^{r^*}, \tag{30}$$

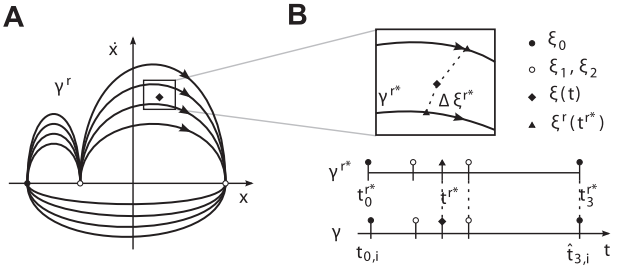

Figure 8. Classification-based event prediction. (A) Family of $R = 4$ limit cycles γ^r with differing periods T^r. In the position-velocity state space, shapes differ due to $\dot{x}$ scaling with T^r. (B) Close-up illustrating distance-based classification *(top)*. Events are predicted based on the acquired evolution of events in γ^{r^*} *(bottom)*.
doi:10.1371/journal.pone.0095195.g008

where $t_l^{r^*}$ denotes the corresponding event in γ^{r^*} and t^{r^*} the time at minimum distance $\Delta\xi^{r^*}$ in γ^{r^*}, see Fig. 8(b).

Note. The quality of the event predictions depends on the number of reference limit cycles and their distribution of periods, i.e. how fine-grained the covered portion of the state space is sampled.

From Phase to Movement

Robotic agents implementing the synchronization behavior require the transformation inverse to the previous one as well. By means of a technique based on movement models, the process variables are transformed back to the cyclic movement trajectory representing the individual action task. After defining the required model properties, we develop an exemplary realization of this transformation through a model based on the minimum-jerk criterion [53]. It renders human hand movements in goal-directed tasks [54].

General movement model. The trajectory is again composed by a given number of L primitives μ_l, $l=1,...,L$ connecting the segmentation points $\boldsymbol{\xi}_l$ with relative primitive durations d_l. Inverse to the phase-amplitude decomposition of the cyclic state trajectory, we require the movement model to take the general form

$$\boldsymbol{\xi}=\boldsymbol{f}(\theta,\boldsymbol{d},\Xi). \tag{31}$$

The function $\boldsymbol{f}$ denotes a mapping of the phase θ, the distribution $\boldsymbol{d}=[d_1 \dots d_L]^{\mathrm{T}}$, and the task-related segmentation points $\Xi=[\boldsymbol{\xi}_1 \dots \boldsymbol{\xi}_L]$ onto the continuous state trajectory $\boldsymbol{\xi}$. In brief, an appropriate movement model needs to.

- fulfill the condition (1) for finite periods T,
- facilitate temporal scaling implemented by θ and $\boldsymbol{d}$,
- facilitate spatial scaling depending on Ξ.

Models complying with these properties are discussed in [27]. In the following, we re-parameterize a model $\boldsymbol{\xi}=\boldsymbol{f}(t)$ explicitly depending on time t to comply with (31).

Note. The process variables θ and $\boldsymbol{d}$ implement the degrees of freedom available for the *voluntary* behavior of movement synchronization. The movement model $\boldsymbol{f}$ has to *necessarily* comply with the task-related segmentation points Ξ.

The minimum-jerk model as an example. Human hand trajectories composed of point-to-point movements are known to be successfully reproduced by the minimum-jerk model formulated in a Cartesian frame [53]. With reference to the human-robot experiment described later on, we investigate this polynomial-type model. The state $\boldsymbol{\xi}=[\boldsymbol{x}\ \dot{\boldsymbol{x}}]^{\mathrm{T}}$ is defined, with x and $\dot{x}$ denoting the hand (effector) position and velocity in a Cartesian frame. The movement model (31) is then realized by a sequence of L point-to-point primitives

$$\mu_l : \boldsymbol{x}=\boldsymbol{f}_l(\chi_l)=(\boldsymbol{x}_l-\boldsymbol{x}_{l-1})g(\chi_l)+\boldsymbol{x}_{l-1}, \tag{32}$$

parameterized by $\chi_l \in [0,1]$. The function $g \in [0,1]$ denotes the fifth-order polynomial

$$g(\chi_l)=6\chi_l^5-15\chi_l^4+10\chi_l^3. \tag{33}$$

The start point $\boldsymbol{x}_{l-1}$ and the end point $\boldsymbol{x}_l$ of the primitive μ_l define the segmentation points $\boldsymbol{\xi}_{l-1}$ and $\boldsymbol{\xi}_l$, since (33) implies $\dot{\boldsymbol{x}}_{l-1}=\dot{\boldsymbol{x}}_l=0$. For any choice $\chi_l \propto t$, (32) minimizes the jerk $\dddot{\boldsymbol{x}}$.

Re-parameterization of the minimum-jerk model. The parameter χ_l of the lth primitive (32) is substituted by the process variables θ and $\boldsymbol{d}$, i.e.

$$\chi_l=h_l(\theta,\boldsymbol{d}). \tag{34}$$

If (34) fulfills the condition

$$h_l(\theta,\boldsymbol{d})=1, \tag{35}$$

the subsequent primitive is activated, i.e. the transition $\mu_l \mapsto \mu_{l+1}$ and $\mu_L \mapsto \mu_1$ respectively is triggered, see Fig. 9(a). The substitution h_l in the current period i is realized by

$$h_l(\theta,\boldsymbol{d})=\frac{1}{2\pi d_l}s_l[\theta-\theta(t_{l-1,i})], \tag{36}$$

which is composed as follows. The phase value $\theta(t_{l-1,i})$ obtained from (11) is subtracted to remove the offset at the event of primitive entry $t_{l-1,i}$. The factor $\frac{1}{2\pi d_l}$ scales phase values $\theta \in [\theta(t_{l-1,i}),\theta(t_{l,i})]$ to values $\chi_l \in [0,1]$. The term

$$s_l=\frac{\sum_{j=l}^{L} d_j}{1-\sum_{j=0}^{l-1} d_j'}, \text{ with } d_0' := 0, \tag{37}$$

ensures, that the boundary condition $h_L(2\pi i,\boldsymbol{d})=1$ is fulfilled for any time-varying $\boldsymbol{d}$. With d_j' we denote the actual value that d_j assumed at past transition $\mu_j \mapsto \mu_{j+1}$.

Note. If $\boldsymbol{d}=const.$ holds, $s_l=1$ is satisfied, and the substitution (36) becomes piece-wise linear, i.e. $\chi_l \propto \theta$. If additionally $\dot{\theta}=const.$

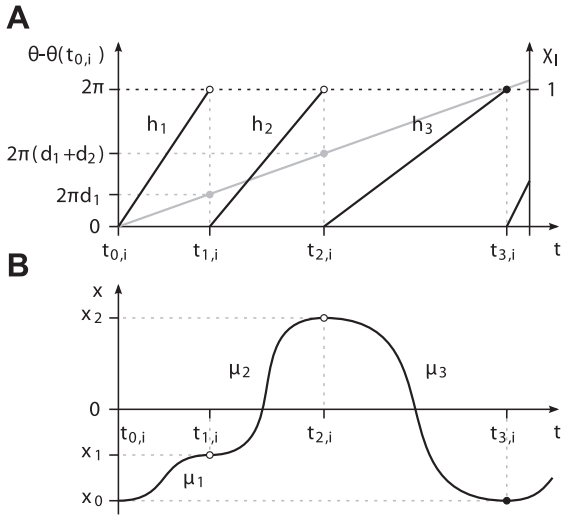

Figure 9. Transformation of the process variables $\theta,\boldsymbol{d}$ into a limit cycle with $L=3$ primitives μ_l. The minimum-jerk movement model is employed. (A) Piecewise-continuous substitutions h_l illustrated for the unperturbed phase with $\dot{\theta}=const.$ (gray graph) and $\boldsymbol{d}=const.$ (B) Continuous, cyclic movement trajectory composed by polynomials f_l. For the corresponding limit cycle representation, cf. γ^b in Fig. 4A.
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holds, piece-wise linear $\chi \propto t$ is obtained. Thus, if the synchronization process is in steady state, the trajectory $\boldsymbol{\xi}(t)$ is composed by minimum-jerk movement primitives, cf. example in Fig. 9.

Human-Robot Synchronization Experiment

The concept of movement synchronization is applied to render the interactive behavior of a robotic agent that performs a joint action task together with a human partner. Supporting information is provided in Video S1. The human-robot synchronization experiment fulfills two goals. First, it provides a proof-of-concept implementation successfully illustrating the developed synchronization behavior by means of a robotic interaction partner. Second, it serves to explore the potentials of the developed robotic behavior in joint action tasks with human interaction partners.

In the following, superscripts [a] and [b] are replaced by [H] and [R] when variables belonging to the human and the robotic agent need to be distinguished.

The Joint Action Task

The design of the experimental task is inspired by the dot-tapping paradigm studied in our previous work [5],[6]. The following points summarize the desired features:

- Both agents perform repetitive movements composed by sequences of *multiple primitives* with closed trajectories (cycles). Multiple cycles performed consecutively allow to study synchronization effects.
- Since we investigate different modes of synchronization, the cycles need to offer potentially relevant *synchronization events*.
- The task is *goal-directed*, i.e. the agents' effectors have to reach one or more goal points.
- *Overlapping workspaces* provoke close interaction and constrain synchronization, since collision avoidance is required in certain workspace regions.
- Mutual pick up of *sensory information* about each others' actions is allowed to let interaction emerge.

Accordingly, the task paradigm depicted in Fig. 10 is designed. Both the human and the robot perform cyclic sequences of multiple movement primitives with their right arm/manipulator, while sitting opposite to each other at a round table. The task is to carry barbell-shaped objects from pick points to place points which are marked on the table. The objects have a height of 140 mm and a weight of 0.19 kg; they are equipped with an iron sheet and a plastic disc on top with reflective markers attached, allowing for magnetic grasping and marker-based tracking respectively. The participant wears a glove with an additional weight and markers attached. Total weight of the glove is 0.51 kg. Its purpose is to naturally slow down the humans' movements. The agents' workspaces are arranged such, that two objects can be exchanged between them in a cyclic fashion. Within each pick-and-place movement, the table shall be touched at a tap point close to the agent. The robot only performs a tap when carrying an object, hence the agents' movement cycles differ. A human-size mobile robot with anthropomorphic arms serves as the interaction partner in the experiment, see Fig. 11.

Three synchronization modes are investigated in the above joint action task, see Fig. 12. These modes synchronize different combinations of pick, place and tap actions. Since the objects can be exchanged by sequential pick-and-place actions, the modes comply with the task-related goals. Note, that each of the segmentation points features two events, entry and leave of the respective point. These frame the so-called dwell time, which is known to be part of human motor control in aiming tasks [55]. The above modes are represented by stable equilibrium relations that are featured by the unified synchronization process, see Table 1. Details on the data acquisition system, the robotic system [56,57] and the implementation of the synchronization behavior of the robot are given in the Appendix S1.

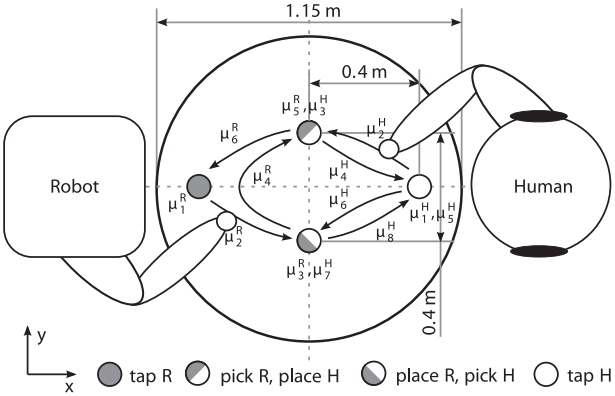

Figure 10. The joint action task designed for the human-robot synchronization experiment. In a symmetric setup, both human and robot perform slightly different action tasks while facing each other. Odd-indexed primitives μ_l consider dwell times, even-indexed ones denote movements. Target points are marked by circles of 115 mm in diameter.
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Participants, conditions and procedure

Participants. Procedures were approved by the ethics committee of the medical faculty of the TUM and conformed to the principles expressed in the Declaration of Helsinki. In total, 12 people (9 female) participated in this experiment. They were between 20 and 48 years old (M = 30.8). All were right handed and had normal or corrected-to-normal vision and were nave as to the purpose of the experiment. For participation, they were paid 8 EUR per hour. Prior to their inclusion in the present study, all participants gave written informed consent. The individual in this manuscript has given written informed consent (as outlined in PLOS consent form) to publish these case details.

Conditions. Two conditions manipulated the synchronization behavior of the robot:

- **NOS**: **No S**ynchronization.

The robot performed at $\dot{\theta}^{\mathrm{R}} = \omega^{\mathrm{R}}$, with constant frequency $\omega^{\mathrm{R}} = 1.3\mathrm{rads}^{-1}$. Its relative primitive durations were set constant to $\boldsymbol{d}_0^{\mathrm{R}} = [0.05\ 0.2\ 0.05\ 0.45\ 0.05\ 0.2]^{\mathrm{T}}$.

- **PES**: **P**hase and **E**vent **S**ynchronization.

The robot aimed to synchronize the three modes we designed above, applying the parameters from NOS and the coupling gains $K = 0.3\mathrm{rads}^{-1}$ and $K_d = 0.02\mathrm{s}^{-1}$.

In both conditions, the effector trajectory of the robot was subject to collision avoidance as described in the Appendix S1.

Procedure. The experimental procedure was as follows. The mobile platform of the robot was maneuvered to a target pose calibrated with respect to the table by means of markers, such that the goal points assigned to the robot were within the workspace of its right manipulator. Similarly, the participants were seated in a comfortable posture close to the table, cf. Fig. 10. A written

Figure 11. Experimental setup. *Left:* The scenario of a prototypical joint pick-and-place task. *Right:* Hand movements are made available to the robot in real time by tracking the glove the human interaction partner is wearing.
doi:10.1371/journal.pone.0095195.g011

instruction handed to the participants provided the description of the human-robot joint action task. In particular, the participants were advised that for the task to be successfully fulfilled, joint action in cooperation with the robotic partner is required. In order to provoke natural interaction, they were instructed to perform at comfortable speed and to touch the marked positions precisely in a single movement. Direct hand-over and sliding the objects over the table was not allowed. The participants were neither informed about the synchronization behavior of the robot, nor were they advised to synchronize. At the beginning of each trial, they were asked to rest with an object in their hand in the respective tap position and instructed to start executing the task as soon as they heard an acoustical start signal (high-pitched tone) through their head phones. The stop signal (low-pitched tone) was presented after they had performed ten cycles. The start signal was timed such that the modes described in Fig. 12 were provoked initially, i.e. for mode 1, both the participants and the robot were triggered simultaneously being in their tap points, for mode 2, the robot was triggered when the participants entered their place points, and for mode 3, the participants were triggered when the robot entered its place point. Six sets (two synchronization conditions × three start-off modes) each consisting of three trials were performed which led to a total of 18 trials. These sets were carried out in a randomized sequence of two blocks, each with three sets under the same synchronization condition. The sets manipulating the start-off mode were presented in randomized order in each block.

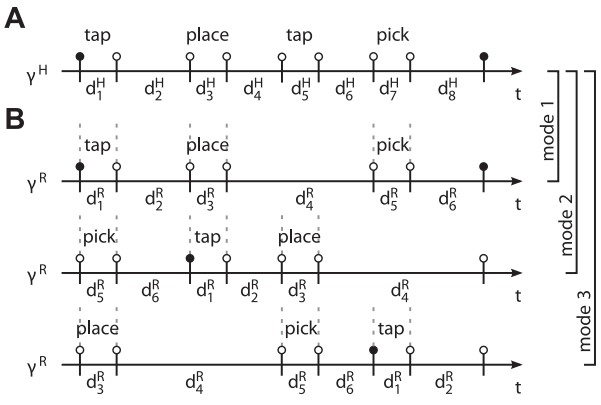

Figure 12. Evolution of events in the experimental task synchronized in three modes. The relative durations d_l correspond to the primitives μ_l defined in Fig. 10. Again, odd-indexed durations are due to expected dwell times in the segmentation points. (A) The cycle γ^{H} of the human. (B) The cycle γ^{R} synchronized to γ^{H} in three different modes, denoted mode 1–3. Vertical dashed lines indicate synchronized events. Intuitively speaking, the human precedes the robot in mode 2 and vice versa in mode 3.
doi:10.1371/journal.pone.0095195.g012

Quantitative Measures

The following measures are deployed to assess the synchronization behavior observed in the experiment.

Event synchronization. The synchronization of events targeted by the behavioral model of the robot is assessed based on the measured Cartesian position trajectories of the human hand $\boldsymbol{x}^{\mathrm{H}}(t)$ and the robot effector $\boldsymbol{x}^{\mathrm{R}}(t)$. Those are recorded simultaneously by the motion capture system, thus differing processing delays are eliminated. Trajectory segmentation and event extraction is identical with the implementation of the robot. According to the definition of event synchronization above, we calculate for each synchronization mode m the temporal lags within all event pairs $(t^{\mathrm{H}}_{l^{\mathrm{H}}}, t^{\mathrm{R}}_{l^{\mathrm{R}}})$ with the indexes $l^{\mathrm{H/R}}$ chosen corresponding to the events synchronized in mode m. For each mode m, the lag magnitudes are averaged per period i^{H}, i.e. over event pairs with $t^{\mathrm{H}}_{l,i^{\mathrm{H}}} \in [t^{\mathrm{H}}_{0,i^{\mathrm{H}}}, t^{\mathrm{H}}_{8,i^{\mathrm{H}}})$. Those averages provide continuous measures of asynchrony, which we denote $\mathrm{ASYN}_{m,i^{\mathrm{H}}}$. In each period i^{H}, the best fitting one out of the three modes is detected by selecting the smallest asynchrony. The per-trial average of the latter over all periods I^{H} reads

$$\mathrm{MASYN} = \frac{1}{I^{\mathrm{H}}} \sum_{i^{\mathrm{H}}=1}^{I^{\mathrm{H}}} \min_{m} \mathrm{ASYN}_{m,i^{\mathrm{H}}}, \tag{38}$$

which we call the mode-related asynchrony.

Note: The mode-related asynchrony quantifies the mean time lag between multiple event pairs measured in seconds. Only complete sets of event pairs corresponding to the defined modes are probed.

Mode distribution and mode switches. At any time, one of three synchronization modes is considered to be *active*, and

Table 1. Stable equilibrium relations of the synchronization process.

Mode	Phase difference $\Phi_{r,e,m}$	Relation of relative durations $d^{H/R}$
$m=1$	$\Phi_{r,e,1}=0$	$d_1^H=d_1^R$, $d_2^H=d_2^R$, $d_3^H=d_3^R$, $d_7^H=d_5^R$, $d_8^H=d_6^R$
$m=2$	$\Phi_{r,e,2}=2\pi\sum_{j=5}^{6} d_j^R$	$d_1^H=d_5^R$, $d_2^H=d_6^R$, $d_3^H=d_1^R$, $d_4^H=d_2^R$, $d_5^H=d_3^R$
$m=3$	$\Phi_{r,e,3}=2\pi\sum_{j=3}^{6} d_j^R$	$d_1^H=d_3^R$, $d_5^H=d_5^R$, $d_6^H=d_6^R$, $d_7^H=d_1^R$, $d_8^H=d_2^R$

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pursued by the robot in condition PES. According to the vector field design cf. Appendix S1 and Table 1, we determine the active mode

$$m=\begin{cases}1, & \text{if } \Phi_r<\dfrac{\Phi_{r,e,1}+\Phi_{r,e,2}}{2}\vee\Phi_r>\dfrac{\Phi_{r,e,3}+2\pi}{2},\\ 2, & \text{if } \Phi_r\geq\dfrac{\Phi_{r,e,1}+\Phi_{r,e,2}}{2}\wedge\Phi_r\leq\dfrac{\Phi_{r,e,2}+\Phi_{r,e,3}}{2},\\ 3, & \text{otherwise.}\end{cases}\qquad(39)$$

Given the evolution of the active mode $m(t)$, we analyze the relative distribution of modes $\frac{N_m}{N}$ as an indicator of the within-dyad preferred synchronization mode, where N_m is the number of samples in active mode m and N the total number of samples per trial. Note that the number of samples is representative of the continuous amount of time spent in a certain mode. Furthermore, the temporal persistence of modes is measured by the number of mode switches, i.e. the number of samples $\{j \mid m(t_j)\neq m(t_{j+1})\}$ per trial.

Synchronization index. Phase synchronization is often quantified by means of the synchronization index, see e.g. [43] for a comprehensive review. Given the time series of the phase difference $\Phi(t)$ consisting of N directional observations $\Phi(t_j)$, the synchronization index

$$\mathrm{SI}=\left|\frac{1}{N}\sum_{j=1}^{N}e^{i\Phi(t_j)}\right|=1-\mathrm{CV}\qquad(40)$$

is calculated, where CV denotes the circular variance of an angular distribution. The synchronization index SI is also called mean phase coherence. The synchronization concept in this article introduces multiple modes, represented by differing equilibrium phase differences. Trials with one or more mode switches would heavily degrade the index (40). Hence, we propose to calculate the synchronization index separately for epochs of the same *active mode*. The resulting indexes SI_m are then combined per trial into the *mode-related* synchronization index

$$\mathrm{MSI}=\frac{1}{N}\sum_{m=1}^{3}N_m\mathrm{SI}_m,\qquad(41)$$

weighted by the respective number of samples N_m.

Note: The MSI lies in the interval [0,1]. Given a perfectly uniform distribution of $\Phi(t)$, it would equal zero. It equals one only if the synchronization process is persistently in steady-state, which means that all samples of $\Phi(t)$ point to the same direction.

Entrainment error of relative primitive durations. As shown in our synchronization concept, the entrainment across the relative primitive durations $\boldsymbol{d}^{H/R}$ is essential to the synchronization of multiple event pairs. It is assessed by the root-mean-square error defined as the residual

$$\mathrm{RMSE}(d_{l^H}^H=d_{l^R}^R)=\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(d_{l^H}^H(t_j)-d_{l^R}^R(t_j)\right)^2},\qquad(42)$$

with the primitive indexes $l^{H/R}$ chosen corresponding to the equilibrium relations summarized in Table 1. For each relation and epoch of the same active mode m, the entrainment errors are obtained from (42) and averaged over the five mode-dependent equilibrium relations afterwards, yielding the errors $\mathrm{RMSE}_{\boldsymbol{d},m}$. Analogously to the above definition of the mode-related synchronization index (41), those are then combined by the weighted average

$$\mathrm{RMSE}_{\boldsymbol{d}}=\frac{1}{N}\sum_{m=1}^{3}N_m\mathrm{RMSE}_{\boldsymbol{d},m},\qquad(43)$$

which assesses the overall entrainment error of $\boldsymbol{d}^{H/R}$.

Experimental Results

The observable degree of event synchronization between the movements is evaluated as *external* measure. Feedback gathered from a short questionnaire is reported as well. We also assess the synchronization behavior through measures relying on *internal* variables of the robot. Note, that the results presented in the following are based on a group of nine participants unless stated otherwise. The remaining group of three participants performed at movement speeds either far below or above the speed range the robot is capable of moving at, thus impeding movement synchronization in the experiment. Possible reasons are discussed later.

External Assessment of the Synchronization Behavior

The following results allow to explain, how far the overall goal of our synchronization concept is reached objectively, i.e. if it fosters the entrainment of movements by synchronizing multiple event pairs. In addition, subjective feedback from the participants gives rise to discuss some perceived effects.

Subjective reasoning. After having completed the experiment, participants were asked whether or not they had the feeling that the robot reacted to them. In case of a positive answer, they were asked to state if they found that perceived reactiveness pleasant (yes/no) and to reason about this answer. Eleven out of twelve participants recognized reactiveness of the robot in response to their movements during parts of the experiment.

Ten out of eleven participants who answered positively stated that they liked the perceived reactiveness, giving reasons such as:

- It makes the robot appear lively.
- Having the control over task speed is pleasant.
- Adjustment towards similar speed is pleasant.
- It fosters smoother interaction.
- Negotiation among partners is beneficial.
- It is a nice feeling, but a bit uncanny as well.

The one who disliked the reactive behavior of the robot described the interaction as flurry and unsteady.

Event synchronization. The evaluation of the objective measure of event synchronization, which is the mode-related asynchrony MASYN, is depicted in Fig. 13. A 2×3 repeated measures ANOVA with the within subject factors *condition* (NOS, PES) and *start-off mode* (1–3) reveals a clear decrease of asynchrony in each of the start-off modes, $F(1,8)=18.06$, $p=.003$, if the robot applies synchronization behavior, i.e. the condition PES. Irrespective of the synchronization condition, start-off mode 1 numerically results in lowest asynchrony values, whereas a slight trend towards increased asynchrony is visible for mode 2 and 3. However, differences between start-off modes were not significant and no significant interaction effect was observed, both $p>.4$.

Internal Assessment of the Synchronization Behavior

In the following, the behavioral dynamics is evaluated based on its internal representation, i.e. the internal variables of the robotic agent.

Entrainment of phases and relative primitive durations. To start, we explain the inner processes governing the synchronization behavior of the robot during an exemplary trial. The trajectories of relevant process variables are illustrated in Fig. 14. After starting off in mode 3, cf. initial phase difference in Fig. 14B, the relation $d_2^{\mathrm{R}}=d_8^{\mathrm{H}}$ is entrained amongst others, see very left part in Fig. 14A. Note that the attractor landscape generated by the vector field H is morphed depending on the entrained components of $\boldsymbol{d}^{\mathrm{R}}$. Thereafter, the phase velocity of the robot $\dot{\theta}^{\mathrm{R}}$ is slowed down by the function $c(\Delta x)$ due to collision avoidance, Fig. 14C. As the participant progresses fast, the robot is forced into mode 1. Through modulation of $\dot{\theta}^{\mathrm{R}}$ within the tuning range $[1,1.6]\mathrm{rads}^{-1}$, which is defined by its natural frequency ω^{R} and coupling gain K, the robot attempts to sustain the mode it is close to. It can be seen, that now the relation $d_2^{\mathrm{R}}=d_2^{\mathrm{H}}$ is pursued. After a while, the participant again increases speed, which leads the robot to finally switch to mode 2. Here, the relation $d_2^{\mathrm{R}}=d_4^{\mathrm{H}}$ becomes entrained.

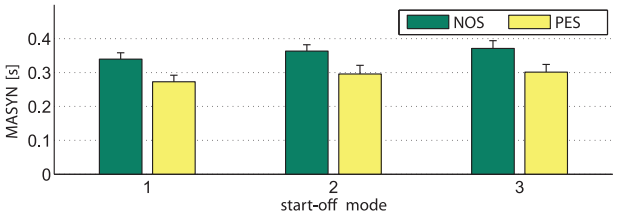

Figure 13. The mode-related asynchrony MASYN. Values are averages over all trials for the three start-off modes under the conditions NOS and PES. The bars represent standard errors of the mean.
doi:10.1371/journal.pone.0095195.g013

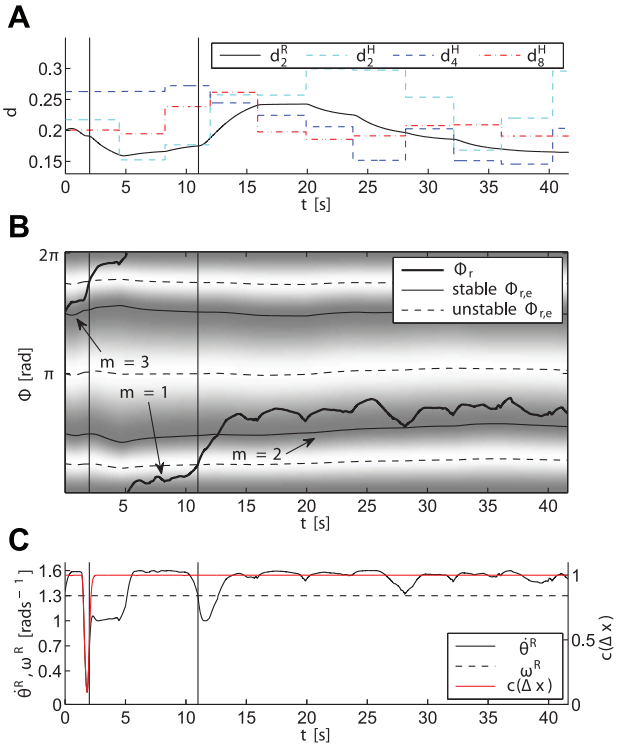

Figure 14. Evolution of selected process variables for a sample trial under condition PES and start-off mode 3. Vertical solid lines denote mode switches. (A) The duration $d_2^{\mathrm{R}}(t)$ of the robot entrained with one of the durations $d_{2,4,8}^{\mathrm{H}}(t)$ of the human, depending on the active mode. (B) The relative phase difference $\Phi_{\mathrm{r}}(t)$, and the vector field H with its time-varying attractive regions (dark) and repulsive regions (bright) representing the modes $m=1,2,3$. (C) The robot phase velocity $\dot{\theta}^{\mathrm{R}}(t)$ and collision avoidance function $c(\Delta x)$.
doi:10.1371/journal.pone.0095195.g014

Preferably synchronized modes. The relative amount of time spent in the synchronization modes and the relative amount of mode switches are illustrated in Fig. 15. Here, the relative time spent in each mode provides an intuition of how long, on average and with respect to the trial durations, each mode has been active within the robot behavior. It can be seen that under PES, the relative share of that mode increases, which the human-robot dyad has started with (upon trigger). To access the differences between NOS and PES with regard to the amount of time spent in triggered mode, planned comparisons were performed between conditions (NOS, PES) within the respective start-off mode. If participants were triggered to start off in mode 1, the relative amount spent in mode 1 is significantly higher under PES compared to NOS, $t(8)=-1.90$, $p=.047$. Since under NOS, the robot only observes but not actively pursues these modes, that increase is due to robotic synchronization behavior in PES. Similar results were obtained for start-off mode 3, $t(8)=-2.57$, $p=.017$. However, the difference between relative mode share in PES and NOS during start-off mode 2 was only found to be numerical, $z=-.77$, $p>.2$. Mode 2 was also the dominant mode during NOS. Hence, no effect of the synchronization behavior is visible here. Overall this shows that when being triggered close to the attracted modes, the robot successfully sustains them.

This is also reflected by the relative share of mode switches. Results of a 2×3 repeated measures ANOVA on condition and start-off mode show that the amount of mode switches decreased

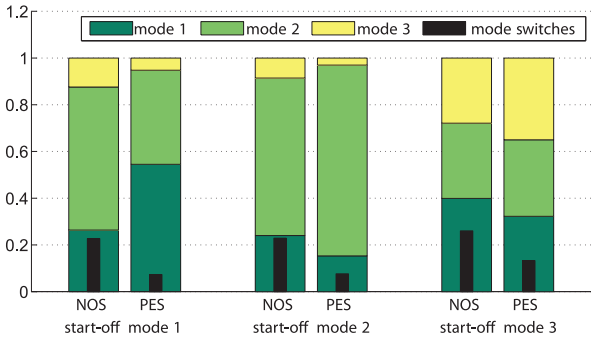

Figure 15. Relative amount of time spent in each mode and relative amount of mode switches. Both are averaged separately over all trials for the three start-off modes under the conditions NOS and PES.
doi:10.1371/journal.pone.0095195.g015

under PES in each of the start-off modes $F(1,8)=17.83$, $p=.003$. Neither a difference between start-off modes nor an interaction effect was observed, $p>.3$.

The preferred phase relations as a result of phase synchronization are reflected by histograms of the phase difference, see Fig. 16 left, which is a representation complementary to the mode distributions above. Some preference towards certain phase relations can be recognized even under condition NOS, which is ascribed to human synchronization attempts due to the static behavior of the robot. Under PES, the distribution gets sharpened, forming three distinct peaks. When comparing that distribution in Fig. 16 left with the distribution of actively attracted equilibrium points in Fig. 16 right, their coincidence indicates successful phase entrainment through the robot behavior. Weight on the peak corresponding to mode 2 (i.e. $\Phi_{r,e,2}$) is strongest, followed by the peak at mode 1 (i.e. $\Phi_{r,e,1}$), which is in line with the distribution of modes in Fig. 15. Note that the smeared distributions of $\Phi_{r,e,2}$ and $\Phi_{r,e,3}$ are due to their dependency on the relative primitive durations $\boldsymbol{d}^{R}(t)$.

Quantitative assessment of the synchronization process. The convergence and performance of the dynamical process of synchronization is measured by means of the process variables, which are the phases or the phase difference Φ respectively, and the relative primitive durations $\boldsymbol{d}^{H/R}$. The results are illustrated in Fig. 17. To access the differences between NOS and PES governed behavior, 2×3 repeated measures ANOVAs were performed with the within subject factors condition and start-off mode. For MSI, the condition PES causes an increased entrainment compared to NOS, $F(1,8)=25.73$, $p=.001$, see

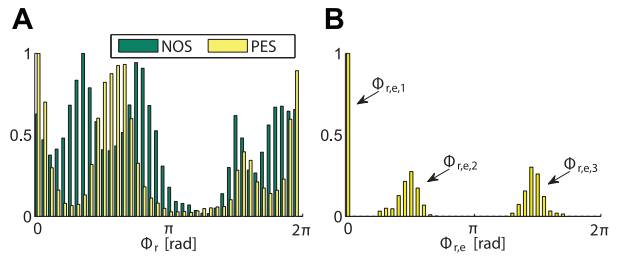

Figure 16. Relative frequencies of occurrence of phase differences. (A) The relative phase difference Φ_r under the conditions NOS and PES. (B) The attracted equilibrium phase differences $\Phi_{r,e}$ under PES.
doi:10.1371/journal.pone.0095195.g016

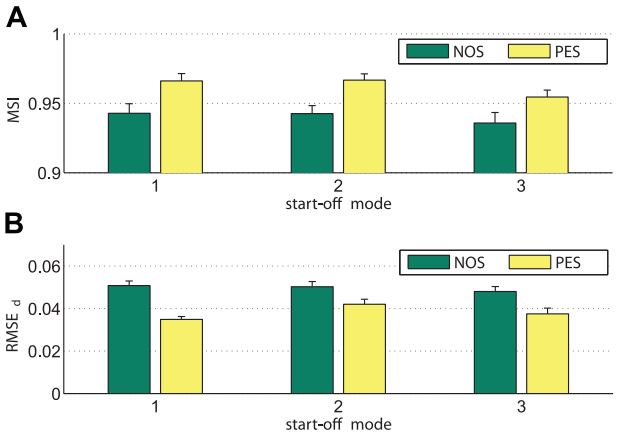

Figure 17. Entrainment measures. Values are averages over all trials for the three start-off modes under the conditions NOS and PES. The bars represent standard errors of the means. (A) The mode-related synchronization index MSI. (B) The root-mean-square error of durations entrainment $RMSE_d$.
doi:10.1371/journal.pone.0095195.g017

Fig. 17A. Between start-off modes no significant difference was observed, $p>.5$. Also no significant interaction effect was detected. Similar results are obtained for the entrainment errors of durations, which are decreased by the entrainment process under PES, $F(1,8)=36.57$, $p<.001$, see Fig. 17B. Lowest errors with respect to the attracted equilibrium relations are achieved in start-off mode 1 under PES, as shown by a significant interaction effect, $F(2,16)=5.29$, $p=.017$.

Instantaneous phase estimation. The characteristic evolution of the period and phase estimation obtained from the human movements are illustrated by means of the sample trajectories depicted in Fig. 18. The events $t^{H}_{8,i}$ result from on-line segmentation of the movement trajectory $y^{H}(t)$, see Fig. 18A. Those events denote the time of the human hand entering the tap point, and the completion times of the periods i. The instantaneous period $\hat{T}^{H}(t)$ depicted in Fig. 18B is equivalent to the prediction $\hat{t}^{H}_{8,i}(t)$, due to the definition of the instantaneous period $\hat{T}^{H}(t)=\hat{t}^{H}_{8,i}(t)-t^{H}_{0,i}$. For comparison, the values T^{H}_{i} measured at period completion are shown as well. Note that due to the finite number of reference cycles used for event prediction, $\hat{T}^{H}(t)$ is not continuous. More specifically, when the reference cycle selected by classification switches, corresponding event predictions switch as well. It can be seen that the on-line estimation of the human phase $\hat{\theta}^{H}(t)$ successfully satisfies our demands: It reflects changes of $\hat{T}^{H}(t)$ instantaneously and smoothly, while it still remains 2π-periodic with respect to the events $t^{H}_{8,i}$ marking the period completions.

Discussion

The results gained from the human-robot synchronization experiment provide the proof of concept and evidence the potentials of synchronization behavior in human-robot joint action. In brief, the following novel insights beyond existing research on movement synchronization are identified: New synchronization modes are explored in the context of goal-directed joint action tasks. The mode-related asynchrony MASYN is successfully decreased by the proposed unified entrainment process of both phase and relative primitive durations. Therefore, the interactive behavior of the robot driven by the proposed

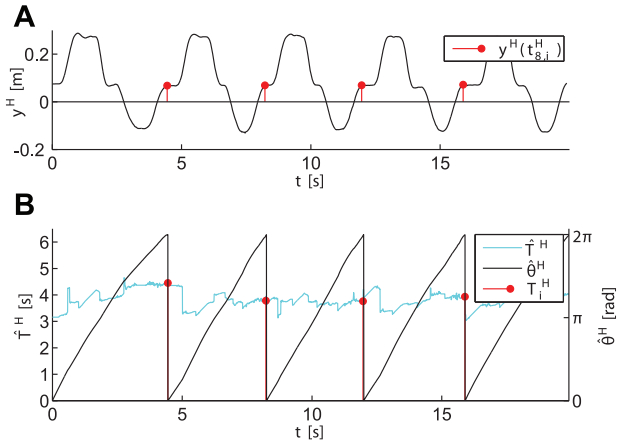

Figure 18. Evolution of the instantaneous phase estimation for the first half of the sample trial. (A) The y-component of the human hand position, and the events $t_{8,i}^{\mathrm{H}}$. (B) The estimated instantaneous period $\hat{T}^{\mathrm{H}}(t)$, the measured period T_i^{H}, and the estimated phase $\hat{\theta}^{\mathrm{H}}(t)$ taken modulo 2π.
doi:10.1371/journal.pone.0095195.g018

concept under the condition PES significantly improves the overall degree of synchronization between the robot and human partners compared to the static behavior under NOS. Mixed discrete and continuous repetitive movement primitives are synchronized in the pick-and-place task. Hence, the novel phase estimation technique is evidently applicable to multi-primitive movement cycles, which cover a wide range of repetitive joint action tasks. Subjective feedback reveals that the synchronization attempts of the robot towards the designed modes lead to an enriched sense of interaction with the robot for most of the participants. This highlights the strong potential of this approach to advance the social interaction capabilities of robots that perform joint actions with humans. In the following, the synchronization concept and the experimental results are discussed in more detail, both in the light of human-robot joint action and the design of interactive behavior for artificial agents.

Implications on Human-robot Joint Action

Both the objective improvement of event synchronization achieved in our exploratory study and the summary of subjective feedback underpin the endeavor to investigate synchronization behavior evident in human-human interaction in the context of human-robot joint action. The behavioral dynamics pursues weak phase synchronization enforced by sinusoidal coupling of strength $K = 0.3\ \mathrm{rads}^{-1}$, which is close to the coupling strengths of uninstructed human-human movement synchronization identified in [6]. Thus, the applied weak forcing is such that participants could not only switch between synchronization modes, they also could have easily resisted or distorted synchronization within the constraints imposed by the hand-overs. In support of this, for a group of three participants we observed that, under PES, the degree of synchronization deteriorated which stands in contrast to the reported improvement of synchronization for the group of nine participants. Most participants appreciated the synchronization attempts of the robot. In short, their answers let us conclude that they had an enriched sense of interaction.

However, the objective results also suggest some implications and pitfalls that need to be addressed carefully in the design of synchronization behavior. Subjectively pleasant, mutual entrainment of movements appears to be rather sensitive to parameterizations of the behavioral dynamics, first and foremost their attractors and their associated strengths. If those do not match the individual entrainment behavior of the human counterpart within certain ranges, inter-agent entrainment may fail and even worse: artificial entrainment attempts may be misinterpreted and lead to a degraded sensation of interaction compared to non-reactive behavior.

The appearance of the robotic partner and, strongly connected, its capabilities anticipated by the participants, is expected to also affect human interactive behavior [58]. Besides its manipulator kinematics having similarity to the human arm, the design of the robotic agent used in our study is rather associated with functional and technical attributes, than with humanoid ones, see Fig. 11. Moreover, we did not brief the participants on the behavior they could expect from their robotic partner. One of the participants reported to perceive some uncanny-ness when facing the reactive behavior of the robot, which could likely be originated by the potential mismatch of rather crude appearance and sophisticated interaction capabilities. Both factors give rise to further investigations going beyond the scope of this study.

Human interactive behavior may furthermore heavily depend on how the task context is conveyed and understood [59]. Human-robot experiments are usually conducted within controlled laboratory settings, which makes it hard to reliably create the desired context in the participants' minds, e.g. that of an everyday activity performed within familiar surroundings. While the implemented behavior is geared towards the abstract context of joint action, emphasis on the individual performance requirements and the cooperative aspect of the task is likely to vary between participants. For example, the instruction to precisely hit designated tap points might be assigned higher priority than an uninstructed and likely unconscious desire to reduce dwell times of the partner in favor of smooth and fluent interaction. All of the above discussed points may affect uninstructed, i.e. emerging synchronization behavior in human-robot joint action. We hypothesize that among those points reasons can be found for the hampered synchronization and behavioral mismatch we observed within the disregarded group of three participants.

Design Issues Regarding the Synchronization Concept

One key idea of the synchronization concept is the design of synchronization modes by means of a dynamical synchronization process unifying both phase synchronization and the entrainment of relative primitive durations. It has to be emphasized that both processes are usually cross-coupled: The entrained components of $\boldsymbol{d}^{\mathrm{a/b}}$ depend on the attracted mode m, cf. Table 1 defining the modes implemented in the experiment. Changes of the relative primitive durations $\dot{\boldsymbol{d}}^{\mathrm{a/b}}$ due to mutual entrainment cause shifts of the equilibrium points $\dot{\boldsymbol{\Phi}}_e^{\mathrm{a/b}}$ within the phase dynamics on the one hand. On the other hand, the attracted mode m is determined by the equilibrium point which is closest to the phase difference Φ. Depending on the designed modes and their attractor dynamics, the interaction of both processes might not be generally stable by itself, and therefore eventually result in oscillations between attracted modes. By defining reasonable bounds $d_{\mathrm{l/h}}^{\mathrm{a/b}}$ and choosing the gain $K_d \ll K$, the entrainment process of durations is bound to certain attractor regions and slow compared to the phase difference dynamics. Though we did not encounter that kind of instability in our experimental setting, the formal derivation of stability bounds remains an open issue.

The presented design of synchronization behavior offers several interesting degrees of freedom which are not investigated in this

article. The structure of the phase synchronization process is originated from the extended Kuramoto model [6] and variants of the HKB model [14] respectively, which evidently replicate human synchronization behavior. In contrast, the implemented entrainment structure of the relative primitive durations is considered prototypical, leaving room for further investigation and validation in the field of human-robot joint action. Similar to the phase dynamics of the HKB model, synchronization modes can be assigned differing weights through variable strengths of attraction. Another degree of freedom is provided by the natural frequency. In line with oscillator theory, the natural frequencies of the harmonic oscillators govern the individual behavior, since they autonomously drive the agents' task progress at their individually desired speed. The domains of successfully negotiated entrainment between the agents is defined by the frequency difference.

Since the definition of the instantaneous phase purely depends on recurrent events within the period, the movement trajectory can be of arbitrary shape, as long as predictions of those events are provided. Instead of the presented technique based on minimum distance classification in the state space, the application of machine learning techniques such as programming by demonstration [60] could be investigated alternatively, for the sake of a flexible encoding of observed movement sequences and event predictions.

Summary and Conclusion

In this article, we propose a novel concept and design methodology to synthesize goal-directed synchronization behavior for robotic agents in repetitive joint action tasks. Those tasks are assumed to be performed by dyads of agents in a common interactive setting. We only require the tasks to be described by closed trajectories in state spaces, where the states capture the relevant movements. Based on oscillator theory, the closed state trajectories are interpreted as limit cycles, for which corresponding phase variables are derived. The sought phases reflect the expected non-stationarity in the limit cycles instantaneously, or in other words, they are defined on a within-period scope and determined on-line. Goal-directed repetitive movements are shown to contain much richer information concerning synchronization than purely their oscillating property captured by the phase variable. Through segmentation, we split complex movement trajectories into sequences of multiple primitives, which are separated by events, e.g. the occurrence of points with zero velocity. Beyond in-phase and anti-phase known from harmonic oscillations, enhanced synchronization modes within limit cycle pairs are synthesized. Their definition utilizes both continuous phases and discrete events as anchoring points for synchronization. The key idea of the synchronization concept is the design of interactive behavior synchronizing the synthesized modes by dynamical processes. In a unifying view, the entrainment of both phases and primitive durations is designed to happen simultaneously on a continuous time scale, as mutual state feedback is assumed to be continuously available to the agents. Inverse to the phase estimation problem, action taking of the robotic agent governed by the synchronization behavior is addressed as well. In the prototypical scenario of a repetitive pick-and-place task, we enable a full-sized, anthropomorphic robot driven by the synchronization concept to cooperate with a human partner. Both objective synchronization measures and subjective feedback evidence effectiveness of the synchronization behavior. Besides the proof of concept, the results gained from the exploratory study highlight the potential of the synchronization concept to enhance the social competence of robots interacting with humans.

The continuous attractor dynamics of the synchronization behavior facilitates the intuitive and systematic design of goal-directed movement coordination. Therefore, the synchronization concept is considered as a promising enhancement to the approach of central pattern generators in the field of robotics. Applications ranging from intra- to inter-agent action coordination are worth looking at in this line of research. We expect the risk of mutual entrainment mismatch in human-robot interaction to diminish, if the behavioral rules of entrainment are derived from observations of human-human interaction. Furthermore, humanoid robots as interaction partners should be employed in realistic joint action scenarios, in order to ultimately disentangle the effects of robotic motor coordination on human-robot joint action.

Supporting Information

Video S1 Details of the experimental scenario and the implementation.
(MP4)

Appendix S1 Experimental setup and implementation.
(PDF)

Acknowledgments

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Author Contributions

Conceived and designed the experiments: AM TL SH. Performed the experiments: AM TL. Analyzed the data: AM TL. Wrote the paper: AM TL SH.

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Appendix S1 - Experimental setup and implementation

Experimental setup

Motion capture system

A marker-based motion capture system *(Qualisys)* is employed to visually track the Cartesian positions of the moving bodies, i.e. the human hand, the robot effector and the objects. The motion capture system consists of ten networked cameras *(Qualisys Oqus 4)*, that are mounted approximately 3 m above the work space and distributed on a square of approximately 10 m × 10 m. Prior to the experiment, the system is calibrated within the work space by means of a manual calibration routine, which guarantees an accuracy < 3 mm. A set of four passive markers is rigidly attached to each body to be tracked in a unique geometrical configuration for proper identification. Ball-shaped, reflective markers of 12 mm and 20 mm diameter are used. The software suite *Qualisys Track Manager (QTM)* for interaction with the system runs on a *Microsoft Windows*-based personal computer. It provides the capture data of the three-dimensional body coordinates with respect to the Cartesian frame attached to the table center. Via the real-time interface, capture data are made available to the robot on-line at a frequency of 200 Hz and at low latencies through a network connection. Low-pass filtering is applied to the data using a 25-point moving average FIR filter at a sampling rate of 1 kHz.

Robotic agent

The human-sized mobile robot is equipped with a pair of seven degrees-of-freedom manipulators [56] of anthropomorphic dimensions. An admittance-type control scheme based on a wrench sensor *(JR3)* in the wrist of the robot realizes compliant behavior of the manipulator when touching the environment. The effector of the right manipulator is equipped with an electromagnetic gripper which allows fast grasps and releases of ferromagnetic objects. A marker-to-effector calibration routine enables robust vision-guided grasping of marked objects by minimizing the error between marker positions and the effector position the manipulator is controlled to. Details on the software architecture can be found in [57]. The algorithms implementing the estimation of the human phase, the synchronization processes, the trajectory generation and the manipulator control scheme are developed in *MATLAB/Simulink*. Utilizing *MATLAB Real-Time Workshop*, the corresponding routines are executed at a sampling rate of 1 kHz on the on-board PCs of the robot running *Ubuntu Linux*. The overall processing delay between perception and action is approximately $\Delta t_{\mathrm{p}} = 30$ ms, which is the average time elapsing from marker movement until movement response of the robot.

Implementation

Design of the synchronization behavior

The vector field H is designed, which defines the phase difference dynamics $\dot{\Phi} = \Delta\omega + H(\Phi)$, with the phase difference $\Phi = \theta^{\mathrm{H}} - \theta^{\mathrm{R}}$. The unstable equilibrium points separating the regions of attraction are equally spaced between the stable equilibrium points given in Table 1, see Fig. S1. By splitting the phase difference dynamics under the assumption of isotropic coupling, we obtain the cross-coupled phase entrainment process

$$\begin{aligned} \dot{\theta}^{\mathrm{H}} &= \omega^{\mathrm{H}} + \frac{H(\theta^{\mathrm{H}} - \theta^{\mathrm{R}})}{2} \\ \dot{\theta}^{\mathrm{R}} &= \omega^{\mathrm{R}} - \frac{H(\theta^{\mathrm{H}} - \theta^{\mathrm{R}})}{2}. \end{aligned}$$

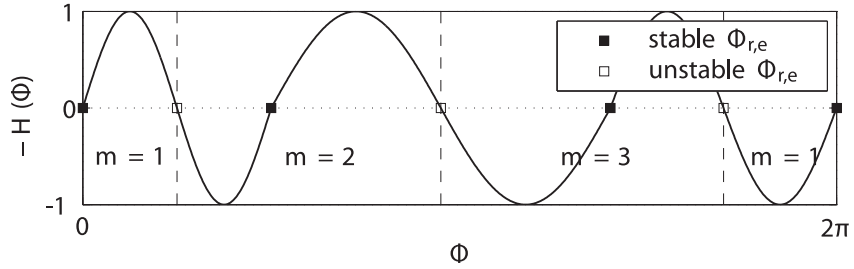

Figure S1. The vector field function H designed by continuous concatenation of sine periods. The stable equilibrium points are chosen according to Table 1. Vertical dashed lines separate the regions of attraction for the case of equal frequencies $\Delta\omega = 0$ and define the active mode m. The plot is parameterized by unit amplitude and $\boldsymbol{d}^{\mathrm{R}} = [0.05\ 0.25\ 0.05\ 0.4\ 0.05\ 0.2]^{\mathrm{T}}$.

The processing delay Δt_{p} of the robot is compensated by adding the constant phase shift $\Delta\hat{\theta}^{\mathrm{H}} = \omega^{\mathrm{R}}\Delta t_{\mathrm{p}}$ to the human phase estimate $\hat{\theta}^{\mathrm{H}}$.

The entrainment process of the relative primitive durations is realized according to the above developed example, i.e. according to (22) and (23). Within the regions of attraction defined by the lower bounds $\boldsymbol{d}_{\mathrm{l}}^{\mathrm{R}} = \frac{1}{2}\boldsymbol{d}_0^{\mathrm{R}}$ and the upper bounds $\boldsymbol{d}_{\mathrm{h}}^{\mathrm{R}} = \frac{3}{2}\boldsymbol{d}_0^{\mathrm{R}}$ around the initial values $\boldsymbol{d}_0^{\mathrm{R}}$ and depending on the active mode m, the equilibrium relations summarized in Table 1 are attracted.

Transformation between movement and phase

The instantaneous phase estimate $\hat{\theta}^{\mathrm{H}}(t)$ is determined according to the classification and prediction technique proposed above. The state $\boldsymbol{\xi}^{\mathrm{H}} = [y^{\mathrm{H}}\ \dot{y}^{\mathrm{H}}]^{\mathrm{T}}$ is defined, with y^{H} and $\dot{y}^{\mathrm{H}}$ denoting the y-components of the tracked Cartesian position and velocity of the human hand. Velocity is obtained from numerical differentiation. For on-line segmentation, the threshold velocity $|\dot{y}^{\mathrm{H}}| = 0.03\,\mathrm{ms}^{-1}$ is used. Event prediction for phase estimation is performed based on $R = 21$ reference limit cycles that have been generated by the minimum-jerk movement model, see Fig. S2. The weighing of position and velocity is defined by the matrix $Q = \mathrm{diag}(1, 0.7)$. The metric difference threshold is set to $\Delta\xi_{\mathrm{th}} = 0.05$. The relative primitive durations are sampled at completion of each cycle i, i.e. $\boldsymbol{d}^{\mathrm{H}}(t_{8,i})$, through on-line segmentation of the human trajectory and averaged over the last three values.

The effector trajectory of the robot is realized by the minimum-jerk model described above, which yields the fixed path depicted in Fig. S3. The pick positions of the objects are visually tracked during interaction, whereas the place positions are calibrated in advance via markers.

Collision avoidance

Whenever the effector is close to either the human hand or to an empty pick/occupied place position, the phase velocity of the robot is modulated by

$$\dot{\theta}^{\mathrm{R}'} = c(\Delta x)\dot{\theta}^{\mathrm{R}}.$$

Depending on the Euclidean distance Δx between the effector position and the human hand or the occupied/empty goal points, the smooth blending function

$$c(\Delta x) = \begin{cases} 0, & \text{if } \Delta x < \Delta x_{\mathrm{l}}, \\ \frac{1}{2} - \frac{1}{2}\cos\left(\pi\frac{\Delta x - \Delta x_{\mathrm{l}}}{\Delta x_{\mathrm{h}} - \Delta x_{\mathrm{l}}}\right), & \text{if } \Delta x_{\mathrm{l}} \le \Delta x < \Delta x_{\mathrm{h}}, \\ 1, & \text{otherwise} \end{cases}$$

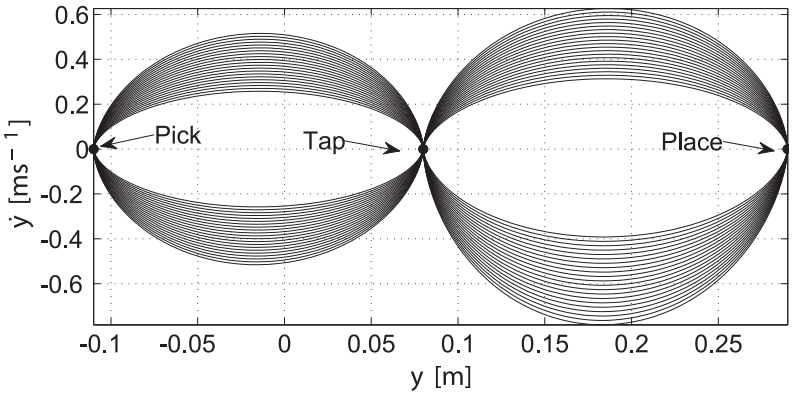

Figure S2. Phase plot of the family of reference limit cycles. Phase velocities $\dot{\theta} \in [1, 2]$ rads^{-1} are chosen equally distributed. Positions are expressed in the table-centered frame, which is aligned to the frame in Fig. 10. The primitive durations are set to $\boldsymbol{d}_0 = [0.05\ 0.2\ 0.05\ 0.16\ 0.05\ 0.22\ 0.05\ 0.22]^{\mathrm{T}}$. Those and the segmentation points denoted by filled dots are mean values which resemble the observations made from pilot trials with a human experimenter.

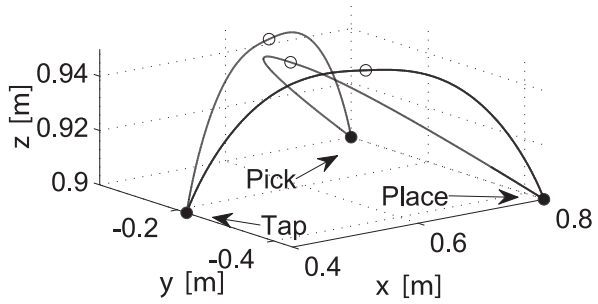

Figure S3. Cyclic effector path of the robot obtained from the minimum-jerk model, expressed in robot coordinates. Filled dots denote segmentation points, open dots denote via points with relative elevation of 0.05 m above the xy-plane.

is applied, which implements a simple collision avoidance behavior. Within the upper distance bound set to $\Delta x_{\mathrm{h}} = 0.25\,\mathrm{m}$, the phase velocity $\dot{\theta}^{\mathrm{R}'}$ is gradually slowed down to zero, reached at the lower distance bound $\Delta x_{\mathrm{l}} = 0.15\,\mathrm{m}$.

Part III

DISCUSSION & CONCLUSION

9 DISCUSSION

Some unspoken human communication is taking place on a hidden channel.
I did not realize they communicated this much without words.
I note that we machines are not the only species
who share information silently, wreathed in codes.

— Daniel H. Wilson, from a robot's perspective

This wirk outlines an iterative approach to derive natural and intuitive human-robot interaction based on human movement synchronization. With regard to human interaction principles, two different theories on how coordination is established, are introduced: the ecological and the cognitive approach. While the ecological approach states that necessary mutual adaptation to establish behavioral coordination is subject to self-organization and can be modeled by means of dynamical systems (Schmidt and Richardson, 2008), the cognitive approach assumes that information processing is required in terms of representations and action plans. In order to establish motor synchrony, the latter suggests linear methods of error correction (Repp and Su, 2013). However, regardless of the obvious differences, both approaches acknowledge the importance of movement synchronization as one of the key elements of human interaction, both with regard to behavioral and social implications.

Having the idea of smooth and natural human-robot interaction in mind, the implementation of movement synchronization would come at multiple benefits (Marin et al., 2009). Besides improving joint task performance, it might increase safety during interaction due to increased predictability on both sides and even have an impact on the acceptance of the robot. When thinking about scenarios of human-robot joint action one could picture a household robot helping to set a table, a robot in an industrial setting in which humans and robots work together or a robot even assisting in training and rehabilitation of activities of daily living. Most of these tasks are in fact pick-and-place tasks which require precision and coordination during goal-directed actions that are necessary when picking an object or placing it at a dedicated position, see also Section 1.1.1.

Therefore, the first experiment reported in Chapter 4 explored the so far untested question whether people synchronize their movements in a cyclic, but goal-directed tapping task. The task is comparable to a pick-and-place task in that it requires precisely directing one's movements to a target location. If two humans perform the goal-directed tapping simultaneously, their movements quickly synchronize. However, if in the same experimental setup, a human is to interact with

a robot that performs repetitive actions, synchronization does not emerge Chapter 5, at least not in the same way.

Obviously, from the human perspective the robot lacks a certain ability or feature that conflicts with or restrains the emergence of movement synchronization.

9.1 FAILING MOVEMENT SYNCHRONIZATION IN HRI

Wheatley et al. (2012) argue that the prerequisite for emerging synchrony between two agents is the attribution of a mind to the respective other, i.e. the capacity to ascribe mental states to others in order to predict or explain their behavior (*theory of mind*) (Keysar et al., 2003; Vogeley and Bente, 2010). Among humans, the formation of a mind attribution involves different factors like lively eye contact and facial appearance, human-like voice, but also and foremost: motion. It seems that mind attribution in humans requires movement profiles that we attribute life to (Chaminade et al., 2005; Kilner et al., 2007; Stanley et al., 2007), and Wheatley et al. (2012) argue that humans use these life-like features to disentangle living beings from artificial objects like puppets. Thus, the creation of artificial agents, which are in the meta layer between living beings and artificial objects, has to make use of these features or might even need further or different cues (Vogeley and Bente, 2010). However, when designing robots and their behavior, the inclusion of live-like features seems tricky: Not enough and the robot remains a machine in human eyes, too much and it might over-exaggerate. Besides, there is the possibility of being close to the correct feature reproduction, but due to a lack of fine-tuning or the neglect of other, usually combined features, the behavior or appearance of the robot is perceived as uncanny (Marin et al., 2009; Mori et al., 2012). With regard to mind attribution to a robot, findings are therefore contradicting. Some studies find evidence for it (Gazzola et al., 2007; Hogeveen and Obhi, 2012; Oberman et al., 2007), some seem to disprove it (Kilner et al., 2003; Press, 2011).

An interesting illustration of this dilemma are the contradicting findings of Kilner et al. (2003) and Oztop et al. (2005). Both studied the emergence of an interference effect, see Section 1.2.3. While the effect was absent in the study by Kilner et al. (2003), it was found in the study of Oztop et al. (2005). Kilner and colleagues argued that humans would not react to artificial motion and that the interference effect is limited to biological motion. However, their robot was a very simple, rather industrial version and probably it was hard to attribute any mind or intelligence to it (Chaminade, 2011). In contrary, Oztop and colleagues replicated the study with the humanoid robot DB (Atkeson et al., 2000) and used recorded human motion profiles as basis for the robot motion generation. Taken together, these findings illustrate that either one of the two factors anthropomorphism or

motion profile, or more likely both, play a role if the robot should be perceived as *having a mind* and subsequently as a social entity (Chaminade et al., 2005, 2012).

Critical with regard to the motion profile is that it appears self-propelled and animate (Cicchino et al., 2011). In HRI that is usually not a problem as robots do perform self-propelled movements and act autonomously. Even if they are programmed, they do not appear to be steered. Besides, humans are able to recognize biological motion already if only minimal information is available such as in point-light displays (Beauchamp et al., 2003; Ulloa and Pineda, 2007). Here, possible cues are micro-movements and unpredictable or intentional behavior due to non-Newtonian velocity changes (Scholl and Tremoulet, 2000; Tremoulet and Feldman, 2006; Waytz et al., 2010).

As these features are obviously important for attributing a life-like behavior to a robot and thus the emergence of movement synchronization, in the current work they were replicated based on human data and previous findings. First of all the robot was performing self-propelled movements which were generated to follow minimum-jerk motion profiles. Minimum-jerk trajectories are known to replicate biological arm motion (Flash and Hogan, 1985) and to cause less irritation for interaction (Huber et al., 2013). Furthermore, a variability was introduced to the via-point (the maximum amplitude) and the target-hitting accuracy of the robot. Nevertheless, the sum of these features did not enable movement synchronization between human and robot to emerge, see Chapters 4 and 5. Here, although we tried to include target variability and via-point variability into the robot's motion, it might be that the variability was still too random or too smooth and thus did not activate the neural representation of animate motion (Beauchamp et al., 2003; Ulloa and Pineda, 2007). These behavioral variations have to be treated carefully also for further reasons: humans use features like amplitude height for demonstrating intentions (i.e. where to move to) (Vesper and Richardson, 2014), or even the breakdown of synchrony as a means for communication (Wheatley et al., 2012). In this line, faster movements during a synchronization process could mark a perturbation and for example be meant as encouragement for the interaction partner to move faster as well. Thus, the variability of amplitude height as implemented in the present experiments could have led to a misinterpretation of behavior instead of supporting it.

Despite the movement profile, it was shown that a human-like appearance of the robot is relevant for mind attribution (Saygin et al., 2011; Shen et al., 2011; Walters et al., 2009). Although it was shown that people have a general tendency to anthropomorphize technology in general (Reeves and Nass, 1996) (but see Dautenhahn (2007)), it seems understandable that an unfamiliar man-size robot like the one used in this work is potentially rather treated with care. Although

the robot has two arms that are able to perform with seven degrees of freedom, it is appearing rather industrial and only to a limited extent humanoid (Althoff et al., 2009; Rohrmüller et al., 2010). Nevertheless, Huber et al. (2013) could show that human-like features improve the interaction, even with a tall and bulky robot - and even independent of its movement profile.

Another important feature for the emergence of synchrony between humans is joint attention. In a study by Schmidt et al. (2007) in which participants were instructed to track a moving stimulus on a screen while swinging a hand-held pendulum, it was found that synchronization between the attended stimulus and the pendulum swinging emerged without being instructed before. Thus, people do actually synchronize to obviously non-living systems if they shift their attention towards them by means of gaze (Richardson et al., 2005; Schmidt and Richardson, 2008). Thus, although in the present experiments participants were always able to observe the robot's movements, the focus of human attention was not shifted to the robot and humans were also not instructed to consider the robot as part of their task. Further investigation should clarify if humans-robot movement synchronization would naturally emerge if the human's attention is shifted towards the robots endeffector. This is especially interesting as it was already shown that the shift of attention is influenced by mind attribution in human-robot interactions (Wykowska et al., 2014).

Besides these rather general aspects, also rather profane reasons may have played a role for the failure of HR movement synchronization in Chapter 5. So far analysis focused only on 1 : 1 movement synchrony with stable states in in-phase or anti-phase relation, which was not observed in the interaction data. However, if a start delay was introduced, the distribution of relative phase shows a peak in the 90° region, usually considered to be the most unstable state of the interaction (Fontaine et al., 1997; Wilson et al., 2005). Here, one possible explanation is that due to the rather low frequency of the robot, humans adapted towards a higher order rhythm which is not captured with the provided analysis.

Furthermore, although the robot's arm has a similar amount of degrees of freedom as the human arm, its joints are rather bulky and it might have been hard for participants to map the expected movement abilities to the actual performance. As humans use their own body schema to predict the behavior of their interaction partners (see Section 1.2.3), this might have led to a correspondence problem (Alissandrakis et al., 2004) and thus to an error in event prediction of the robot's behavior, which would explain a shift in the relative phase.

Finally, it is possible that humans actually did behave towards the robot in the same way as they behave in human-human interaction. As mentioned previously humans use motion profiles to communicate intentions (Vesper and Richardson, 2014). Thus the phase shift

observed in the data could be explained by the fact that humans tried to encourage a response from the robot by adapting their motion primitives (de Rugy et al., 2006). If this is the case, then the synchronization process did not fail due to the wrong motion profile or appearance of the robot, but due to its non-responsiveness (Kose-Bagci et al., 2010).

9.2 MUTUAL ADAPTATION AND RECIPROCITY

The robot used in the experiment in Chapter 5 moved at a constant frequency, namely the mean frequency identified in human-human interaction of the first experiment (Chapter 4). Although being totally visible for the human, the robot did not react to the human action, it acted non-adaptive. Thus, there was no reciprocity or mutuality involved which apparently caused the human and the robot to act *next to each other* instead of forming a dyad. And even if the human attempted to adapt, he/she would immediately perceive the lack of feedback as the robot would just maintain its movement frequency.

9.2.1 *Lessons Learned from Human Interaction*

Humans seem to start their own adaptation to the joint action process only if they perceive the reciprocity of their actions (Frith and Frith, 2010; Sacheli et al., 2012). Only then people apparently take an effort and adapt to another person and even help others to compensate an arising difficulty by motor adjustments and making themselves more predictable for the interaction partner (Vesper et al., 2011), see also Chapter 6.

According to the ecological approach, human interpersonal adaptation is emerging as a result of the self-organization of the interaction (Schmidt and Richardson, 2008). Here, it is assumed that what is modeled is not the sum of components - but the outcome of the interaction (Vallacher and Jackson, 2009; Vesper et al., 2010). Nevertheless, if this approach should be involved in the design of human-robot interaction, it needs to be disentangled to a certain extend as the robot needs a behavioral concept it has to follow if the interaction should emerge on basis of *online* mutual adaptation.

Thus, in order to gain insight into human adaptive principles, participants' movements during HHI were segmented into motion primitives, namely dwelling and moving primitives. An experiment was designed in which increased adaptation was necessary for the emergence of synchrony due to the need of one participant to move around a stable obstacle (Chapter 6). It was found that while the free actor (without obstacle) increased dwell times and besides that moved at constant and unaffected velocity to remain predictable, the hampered actor increased his/her velocity and decreased dwell times to com-

pensate for the extended trajectory due to obstacle avoidance. Furthermore, the free actor marginally extended his/her movement trajectory in response to the extended trajectory of the hampered actor.

These results can both be interpreted in the light of ecological and cognitive approaches. As discussed in Chapter 6, the marginal extensions of the free person's movement trajectory could be due to movement interference (Kilner et al., 2003; Stanley et al., 2007) or the representation of the other's task in spatio-temporal forms (van der Wel et al., 2007) and thus related to motor contagion (cognitive approach). Alternatively, the extended trajectory could be a result of increased deviations due to rhythmic movement interference (Fink et al., 2000; Milliex et al., 2005; Richardson et al., 2009; Romero et al., 2012) which states that while observing incongruent movements to the own ones, additional degrees of freedom are liberated (which result in the deviations) to stabilize the coordination (ecological approach). Without wanting to be exclusive, the latter explanation seems more plausible in the light of the observed dwelling behavior. If the movement interference would cause the extended trajectory then this effect would actually hinder emerging synchronization instead of supporting it and furthermore, the complementary dwelling behavior observed by participants would loose its purpose.

However, regardless of the approach taken, what is clear is that people apparently make use of different adaptive strategies within discriminable motion primitives.

9.2.2 *Mutual Adaptation for Human-Robot Interaction*

As mentioned above, for successful emergence of human-robot coordination it is necessary that the robot can contribute to the reciprocity of the interaction, that it can adapt to human behavior.

Using data from the HHI task described in Chapter 4, it was shown that goal-directed movements can successfully be replicated by the extended Kuramoto model, a coupled oscillator approach which was inspired by the HKB model (Haken et al., 1985; Kuramoto, 1984), Chapter 7. The two oscillators, representing the movements of the human and the robot respectively, are connected by a coupling function. During interaction, the coupling gain determines the adaptivity of the robot towards the human as it scales the detuning of the relative phase towards the attractor state. Offline, the model was shown to successfully replicate the human interaction data in goal-directed tasks. However when applied online in human-robot interaction, a further problem became prevalent: namely that even if the robot's adaptation is scaled by the coupling gain, the acceptable amount of this gain still has to be determined, see also (Oullier and Kelso, 2009).

Repeating the experiment again, now with the ability to adapt its behavior, in Section 7.3 it was shown that the fact that people rec-

ognize that the robot adapts to them actually changes their behavior in an unexpected way. For the group that did not perceive that the robot adapted its behavior to them (Group I (N)), synchronization peaks become more and more prevalent with increasing coupling gain. The fact that mainly anti-phase relation is established could result from the people's natural urge to keep a safety distance from the robot due to its appearance. Nevertheless, synchronization is successfully established. In contrast, the distribution of relative phase for the group who did recognize the robot's adaptation (Goup II (Y)) reveals a rather strange or shifted distribution for higher coupling gains, while lower coupling did not seem to support the emergence of synchronization. With increasing coupling gain, the robots adaptive behavior became more and more obvious to participants and they suddenly moved faster or slower during motion primitives or extend their dwelling primitives beyond practical use to explore how the robot reacts to these changes. Thus, they constantly disturbed the phase relation that the robot aimed to establish following the interaction model, which causes a shifted peak in relative phase distribution. More generally, people seem to challenge the robots behavior in that they requested the robot to adapt to their behavior by breaking synchrony (Wheatley et al., 2012).

However the latter is rather likely if the interaction was in general rated as pleasant. In contrast, as synchrony relates two agents to each other (Hove and Risen, 2009; Valdesolo and Desteno, 2011), it is possible that those participants which did not rate the interaction as pleasant, actively tried to break synchrony and with this escape from the uncannyness of the interaction. This is also reflected in the cross-spectral coherence. The interaction of people who did realize the robotic adaptation resulted in lower coherence especially for the lower coupling gains. What is interesting is that the coherence from Group I (N) was actually higher from the beginning. This could reflect a more trustful relation to technology or robots in general, while the other group could have been more critical (Waytz et al., 2014).

However, while further research in this line has to clarify if the reaction of those people who did recognize the robot's adaptation is in fact purely related to their urge to explore or to their general curiosity or precaution, the problem of determining the amount of adaptivity remains. And if it is not adjusted in a human-like way, it can lead to unexpected or undesired human reactions and even cause a feeling of uncannyness (Marin et al., 2009; Mori et al., 2012).

What is problematic in this regard is that the amount of adaptivity one expects or wants from a robot might depend on personal preferences (Walters et al., 2007) and the level of experience with regard to the interaction with robots (Goodrich and Schultz, 2007; Press, 2011; Press et al., 2007).

Furthermore, the overall intention of the present work was to introduce a concept for HRI that enables natural and smooth interaction with the goal to establish social and behavioral benefits for HRI. Resulting form the presented research on human interaction, the general hypothesis is that these benefits are established as a response to emergent synchronization, which can only successfully emerge and cause these benefits when it results from mutual adaptation. Although it is know that synchronization can be induced and still causing social benefits like group feelings when intentionally synchronizing during marching or singing together, still a mutual input - a mutual adaptation seems essential. With the presented models and a high enough coupling gain however, it is possible that the robot established the synchronization by itself, i.e without the active response-adaptation of a human. This becomes plausible when looking at the cross-spectral coherence in Section 7.3, Figure 4. For the highest coupling gain, the coherence was similarly high for both groups, even though the distribution of relative phase showed that people who had recognized the robot's adaptive behavior tried to break synchrony. With the high coupling gain however, people were forced into an interaction in which the robot is the leader and overrules human attempts to change. Here, although the benefits for safety such as predictability remain, the social benefits of natural emergent coordination might be lost. Therefore, the necessity arises to disentangle human from robotic adaptation in order to not only determine the correct amount of coupling for the natural emergence of synchronization. Fairhurst et al. (2012) suggested a scaling factor for the adjustment of a virtual agents asynchrony to a human performing a tapping task. It was found that this scaling factor has a defined range in which the human perceives the actions as human-like and thus helpful. Although promising, the findings lack an implementation to an embodied agent. Furthermore it remains to be clarified if the optimal asynchrony adjustment or coupling gain encourages mutuality and thus reciprocity.

9.3 JOINING FORCES FOR EMERGENT COORDINATION IN HUMAN-ROBOT INTERACTION

Resulting form the attempt to capture the underlying principles of human movement adaptation in goal-directed tasks (Chapter 6), it was found that humans adjust their behavior based on motion primitives. Therefore, in addition to continuous methods for phase estimation, also a *hybrid approach* was suggested in Chapter 7. The hybrid approach accounts for primitive durations that are in principle adjustable and with this even extents the applicability of the model to more complex tasks.

Bringing this idea forwards, in the model in Chapter 8, the goal-directed interaction task is again described by closed movement trajectories which are interpreted as limit cycles for which instantaneous phase variables are derived based on oscillator theory. Additionally however, task-relevant events are detected to segment these trajectories into motion primitives. This is in line with recent findings of Studenka and Zelaznik (2011) who showed that synchronization to an external rhythm can be improved by including perceptible events as anchoring point into an otherwise purely continuous movement. Utilizing both continuous phases and discrete events in a unifying view, a continuous dynamical process is designed which allows for the emergence of different modes of synchronization. These modes can be understood as an additional adaptation to task requirements in that they allow for different scenarios in which both the human and the robot can take the lead in the interaction. Here, the robot switches modes based on selecting the smallest asynchrony in an observed period of time, thus successfully combining phase adaptation with ideas from event-based synchronization.

A first proof of-concept study showed that the model can successfully be applied in a human-robot joint pick-and-place task. While all the arguments mentioned above still apply also to the model outlined n Chapter 8, all (exept one) participants who recognized the adaptivity of the robot reasoned positively about the interaction with the robot. Overall, although there are still a lot of open questions with regard to the adaptation behavior of a robot, the models described in Chapters 7 and 8 provide a good starting point for further research. By combining cognitive and self-organizing ideas, the model described in Chapter 8 is capable of both describing the timing of the turn-taking by emergent dynamics and also account for the events of picking and placing objects.

In general the notion of including event-based segmentation into an otherwise dynamical process conflicts with the ongoing debate of keeping self-organizing processes and representations apart, see Section 1.2, as it was argued that self-organizing systems cannot account for more complex and sequential tasks (Sebanz and Knoblich, 2009a). However, our results rather support the notion of Repp and Steinman (2010) who assume that emergent and event based timing can coexist. Especially in the interaction with unfamiliar robots that do not allow for direct motor matching or action simulation due to the correspondence problem (Alissandrakis et al., 2004), it might even be necessary to recruit different resources to enable smooth coordination.

However, although the robots behavior based on the presented models is now potentially more predictable and the interaction between human and robot was shown to be mostly pleasant, it remains to future research if the estimated behavioral and social benefits can be derived from this concept and even more, be maintained for form-

ing a general acceptance of robots in the close surrounding of humans. Nevertheless, at least for the coordination in pick-and-place tasks, it seems beneficial to join forces to enable smooth and intuitively emerging coordination between humans and robots.

10 CONCLUDING REMARKS

In literature and in life we ultimately pursue,
not conclusions, but beginnings.

— Sam Tanenhaus

Robots are more and more entering the human surrounding, be it in private life or in a workplace setting. This creates the need for intuitive and safe interaction principles that both the human and the robot can apply on a daily basis.

In order to achieve this, the current work follows one possible strategy that is utilizing data from emergent human coordination, more precisely the human tendency to synchronize movements, to improve human-robot interaction. Therefore, it was first explored if movement synchronization emerges in goal-directed tasks that share features of pick-and-place tasks, a common activity of daily living. Following this, it was tested if movement synchronization also emerges in human-robot interaction. Here, it was shown that movement synchronization does not emerge without mutual adaptation and also other possible influencing factors were discussed. Thus, human adaptive mechanisms were explored in more detail and two models were developed to capture the interaction dynamics. These models were implemented on a robot and evaluated in applied human-robot interaction.

10.1 LIMITATIONS AND CHANCES OF THE CURRENT APPROACH

With regard to the exploration of the emergent dynamics underlying movement synchronization, one of the main problems is the difficulty to manipulate important variables such as the coupling strength. Despite being a prevalent issue for emergent coordination in human-robot interaction, Oullier and Kelso (2009) also identify this problem for human-human social coordination in general. However, having implemented a system allowing for coupling human action to robotic actions provides an interesting test-bed for this issue. In the current approach, the coupling is scalable and adjustable as are the robot's movement parameters and appearance. Thus, although the second problem Oullier and Kelso (2009) mention – namely controlling the complexity of the interaction system – remains, the current setting at least allows for partial control of parameters. Thus, systematically varying influencing factors might not only lead to an improvement of human-robot interaction, but also to a better understanding of human social coordination.

Apart form this, the underlying psychological, neuroscientific and social principles that inspired the current approach are still not totally understood. Although there is huge effort taken and vivid debate going on, it is for example not totally clear how the mirror neuron system supports the perception and execution of action (Press, 2011). In addition, there is still an ongoing debate on the integration of found principles from the two different approaches on the human ability to interact with others, namely the cognitive and the ecological approach, see Section 1.2. Also here, robots allow for the evaluation of models and theories from both interaction approaches and might even proof to profit from their combination, as shown in Chapter 8.

In order to identify relevant cues for emergent coordination, especially eye-tracking and brain-activity measures seem promising. Gaze is an efficient indicator for a person's attention during interaction (Wykowska et al., 2014), while especially the phi-complex (Tognoli et al., 2007) as an objective neural measure seems promising for detecting human joint versus single action mode in human-robot interaction. In this line it might be worth exploring if and to what extent, adaptivity and joint attention influence and shape each other with regard to emergent coordination.

In addition to these more general concerns, there were some limitations that resulted from the experimental design itself. One is the trial length: here, the general assumption was that the emergence of human movements is a very quick process and data from the first experiment (Chapter 4) seems to support this claim. Thus participants in all reported experiments only performed 10 cycles and data recording was stopped when both interaction partners had fulfilled them. Although human interaction data shows that movement synchronization is established quickly after starting or disturbance of an interaction, it is known that the coordination is loosely coupled and thus transfers between stable states (Schmidt and O'Brien, 1997). Future research has to elicit if, especially in human-robot interaction, movement synchronization can be maintained over extended periods of time, which is crucial for the joint performance of activities of daily living.

Besides, in the current approach, adaptation was understood as an interactive process that should possibly emerge between human and robot. The assumption was, that the adaptation effort, the extent to which bot agents engage in the adaptation is ideally divided among them in equal parts. However this is not necessarily the case. Moreover it is well plausible that adaptation is a dynamic process itself and fluctuating between agents in that one agent leads the other and vice versa. Thus, it might be that it is not scalable in the suggested way and is instead recognized by the human due to its necessity. Warren (2006) suggested that instead the adaptation is a result of the self-organizing process which seeks a stable state in the mutual be-

havior by perceptual motor exploration - which is basically based on trial and error (Newell and McDonald, 1992). In future developments such adaptive behavior could be achieved with reinforcement learning by optimizing an objective function, such as the stability of the interaction (Izawa et al., 2008).

Furthermore, in the current setup, people's actions did not overlap with those of the robot. However in activities of daily living this is often the case. Thus, exploring movement synchronization in goal-directed overlapping actions might be promising, also with regard to the applicability of the proposed modeling approaches.

Finally, none of the presented models acknowledges the adjustment of amplitude height of the movement in a systematic communicative way. As discussed in Section 9.1, humans communicate their intentions with regard to target locations by means of amplitude adjustments (Vesper and Richardson, 2014). Thus including this feature to human-robot interaction seems to be essential for the emergence of natural coordination in human-robot joint pick-and-place tasks and for the acceptance of the robot as a reliable interaction partner.

10.2 CONCLUSION

Overall, the concept to explore human-human interaction in order to use the findings for human-robot interaction remains a challenging yet promising approach. On the one hand it seems that iterative procedures are necessary for linking research in cognitive and ecological psychology, neuroscience and social sciences to robotics. On the other hand, one might not only gain a better understanding of underlying mechanisms and parameters in more detail by using robots as a testbed, but also create vivid agents that support humans by providing service and support in rehabilitation, household and public life.

Having stated this, the current approach which is focusing on a very basic application - the emergence of coordination in a pick-and place task - is one of the very first steps to enable safe and naturally emergent human-robot coordination in order to enrich the human technological surrounding and hopefully, in the long run, increase human quality of life.

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Part IV

APPENDIX

EIDESSTATTLICHE VERSICHERUNG

Hiermit versichere ich an Eides statt, dass ich die vorliegende Dissertation selbstständig angefertigt habe, mich außer der angegebenen keiner weiteren Hilfsmittel bedient und alle Erkenntnisse, die aus dem Schrifttum ganz oder annähernd übernommen sind, als solche kenntlich gemacht und nach ihrer Herkunft unter Bezeichnung der Fundstelle einzeln nachgewiesen habe.
I hereby confirm that the dissertation is the result of my own work and that I have only used sources or materials listed and specified in the dissertation.

Munich, March 31, 2015

Tamara Lorenz

Die Beiträge zu den hier angeführten Publikationen waren wie folgt:
The contributions to the previously quoted publications were as follows:

– PUBLICATION 1 - CHAPTER 4 –

Reference

Lorenz, T., Mörtl, A., Vlaskamp, B.N.S., Schubö, A. & Hirche, S. (2011). Synchronization in a goal-directed task: Human movement coordination with each other and robotic partners. In *20th IEEE International Symposium on Robot and Human Interactive Communication (IEEE RoMan)*, Atlanta (GA), USA, pp 198–203

Contributions

Tamara Lorenz, Björn N. S. Vlaskamp, and Sandra Hirche defined the research question on synchronization in goal-directed tasks. Anna Schubö supported the research question design based on human interaction principles. Tamara Lorenz, Björn Vlaskamp and Anna Schubö designed the experiments. Tamara Lorenz and Alexander Mörtl collected the data. Tamara Lorenz and Björn Vlaskamp analyzed the data. Tamara Lorenz and Alexander Mörtl wrote the paper. Anna Schubö and Sandra Hirche supervised the project.

– PUBLICATION 2 - CHAPTER 5 –

Reference

Lorenz, T., Mortl, A., & Hirche, S. (2013). Movement synchronization fails during non-adaptive human-robot interaction. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, Tokyo, Japan, pp. 189–190

Contributions

Tamara Lorenz, Alexander Mörtl and Sandra Hirche defined the research question on non-adaptive Human-Robot movement synchronization. Tamara Lorenz and Alexander Mörtl conducted the experiment. Tamara Lorenz analyzed the data with support by Alexander Mörtl. Tamara Lorenz wrote the paper with comments of Alexander Mörtl and Sandra Hirche. Sandra Hirche supervised the project.

– PUBLICATION 3 - CHAPTER 6 –

Reference

Lorenz, T., Vlaskamp, B. N. S., Kasparbauer, A.-M., Mörtl, A., & Hirche, S. (2014). Dyadic movement synchronization while performing incongruent trajectories requires mutual adaptation. In *Frontiers in Human Neuroscience*, 8, pp 461. doi:10.3389/fnhum.2014.00461

Contributions

Tamara Lorenz, Björn Vlaskamp, and Sandra Hirche defined the research question on synchronization in goal-directed tasks. Tamara Lorenz, Björn Vlaskamp, and Anna-Maria Kasparbauer designed the experiment. Anna-Maria Kasparbauer, Tamara Lorenz, and Alexander Mörtl performed the experiment. Tamara Lorenz, Anna-Maria Kasparbauer, Björn Vlaskamp, and Alexander Mörtl analyzed the data. Tamara Lorenz, Anna-Maria Kasparbauer, Björn Vlaskamp, Alexander Mörtl, and Sandra Hirche wrote the paper. Björn Vlaskamp and Sandra Hirche supervised the project.

– PUBLICATION 4 - CHAPTER 7 –

Reference

Mörtl, A., Lorenz, T., Vlaskamp, B. N. S., Gusrialdi, A., Schubö, A., & Hirche, S. (2012). Modeling inter-human movement coordination: synchronization governs joint task dynamics. In *Biological Cybernetics*, 106(4–5), pp. 241–59. doi:10.1007/s00422-012-0492-8

Contributions

Tamara Lorenz and Anna Schubö designed the study; Tamara Lorenz and Alexander Mörtl conducted the experiment; Alexander Mörtl, Tamara Lorenz and Björn Vlaskamp analyzed the data; Alexander Mörtl and Azwirman Gusrialdi developed the modeling approach with contributions from Tamara Lorenz and Sandra Hirche; Alexander Mörtl, Tamara Lorenz, Björn Vlaskamp and Sandra Hirche wrote the paper; Sandra Hirche and Anna Schubö supervised the project.

Alexander Mörtl and Tamara Lorenz share first authorship.

– PUBLICATION 5 - CHAPTER 8 –

Reference

Mörtl, A., Lorenz, T. and Hirche, S. Rhythm patterns interaction – synchronization behavior for human-robot joint action., *PLoS One*, vol. 9, no. 4, p. e95195, Jan. 2014. doi:10.1371/journal.pone.0095195

Contributions

Conceived and designed the experiments: Alexander Mörtl, Tamara Lorenz, Sandra Hirche. Performed the experiments: Alexander Mörtl, Tamara Lorenz. Analyzed the data: Alexander Mörtl, Tamara Lorenz. Wrote the paper: Alexander Mörtl, Tamara Lorenz, Sandra Hirche

Munich, March 31, 2015

Tamara Lorenz Alexander Mörtl Sandra Hirche